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Research Article

Vehicle platoon trajectory prediction under traffic oscillation: A causal physics-informed deep learning approach

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ABSTRACT: Autonomous driving based on single-vehicle perception still cannot avoid the negative impacts caused by traffic oscillations when traveling in mixed-vehicle platoons. In this scenario, real-time and accurate prediction of the future trajectories of the vehicle platoon ahead of the autonomous vehicle is key to addressing this issue. However, in mixed platoons dominated by heterogeneous and uncertain human-driven vehicles (HDVs), this remains a significant challenge. Existing model-driven, data-driven, and hybrid approaches often suffer from poor interpretability, weak physical constraints, and insufficient accuracy in dynamic environments. To overcome these limitations, this study proposes a Causal Physical Information Deep Learning Model (CPIDLM) for high-fidelity platoon trajectory prediction. First, CPIDLM constructs a novel causal graph attention mechanism that explicitly captures behavioral heterogeneity and causal interactions among vehicles. Second, a physics-informed enhancement architecture is developed to embed prior knowledge from physical models into the deep learning network. Additionally, a dynamic adaptive weighting module is designed to achieve a dynamic balance between contributions from physical laws and data-driven patterns. Extensive validation based on real-world trajectory datasets shows that, compared to existing models, CPIDLM reduces gap prediction error by 16.7%, significantly outperforming current state-of-the-art methods in accuracy. This study establishes a powerful new paradigm for vehicle platoon trajectory prediction under traffic oscillation scenarios.

KEYWORDS: Physics-informed deep learning, Traffic Oscillation Prediction, Intelligent driver model, Vehicle trajectory prediction

1 Introduction

Autonomous vehicles relying exclusively on local perception remain susceptible to traffic oscillations within mixed-vehicle platoons, primarily due to the heterogeneity and uncertainty of human driving behavior (Gao et al., 2019; Zhao et al., 2024). These oscillations induce speed fluctuations that precipitate various adverse effects, including elevated safety risks, diminished ride comfort, and increased energy consumption (Fang et al., 2023; Yang et al., 2023). Although Internet of Vehicles (IoV) technology enables vehicle-to-infrastructure (V2I) communication and roadside sensing systems can effectively mitigate the limitations of individual vehicle perception, these advances fall short of fundamentally resolving traffic oscillations (Hao et al., 2025). The main challenge lies in the difficulty of achieving accurate, real-time predictions of these oscillations. This difficulty is especially pronounced in mixed traffic flows dominated by human-driven vehicles (HDVs), where the propagation of traffic oscillations exhibits high complexity and uncertainty (Mo et al., 2021; Kang et al., 2023).

As shown in Fig. 1, there are significant differences in the stable following distance, reaction time, and minimum following distance among different drivers within the same platoon. Even for the same individual, the desired following distance and reaction time vary significantly across different speed regimes. This variability underscores the inherent heterogeneity and stochastic uncertainty embedded within human driving behavior. This disparity results in a markedly nonlinear and stochastic transmission of traffic oscillations. Without precise forecasting of oscillation wave transmission, even vehicles equipped with enhanced multi-leading-vehicle awareness cannot make optimal driving decisions to smooth the fluctuations. This complexity presents a significant hurdle to real-time accurate prediction and represents a critical technological bottleneck limiting intelligent connected vehicles (ICVs) from improving safety, comfort, and efficiency in oscillatory traffic conditions (Liu et al., 2025).

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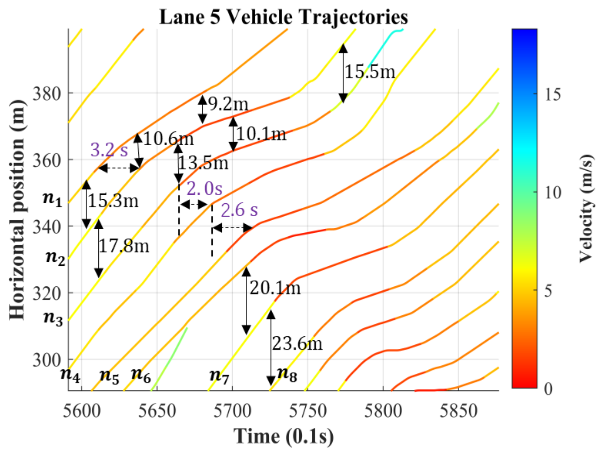


Fig. 1. Differences in Driver Behavior Characteristics (Behavioral Heterogeneity) within the Same Platoon

Extensive research has been conducted on real-time, accurate prediction of traffic oscillations, generally categorized into three approaches: theory-driven models, data-driven methods, and their hybrid integration (Mo et al., 2021; Fang et al., 2023; Hao et al., 2025). Theory-driven models struggle to fully capture the nonlinear nature of traffic oscillations, especially when accounting for diverse driver behaviors and varied traffic scenarios. The Intelligent Driver Model (IDM) and its improved versions are benchmarks in microscopic traffic flow research. While these approaches effectively capture behavioral heterogeneity in simulation through parameter adjustment, they face significant challenges in multi-step trajectory prediction. Specifically, they are unable to rapidly calibrate driver-specific parameters using only brief historical observation windows. Moreover, by assigning static parameter sets to individual drivers, these methods fail to account for the inherent uncertainty nature of human driving behavior (Liu et al., 2023; Zhang et al., 2024). Data-driven approaches, particularly deep learning models, can learn nonlinear traffic flow features from large datasets and demonstrate strong predictive capability in specific scenarios; however, these models often lack adherence to underlying physical traffic laws. It reduces their generalizability and robustness under extreme conditions and may yield predictions that are inconsistent with real-world phenomena. (Zhou et al., 2017; Ma et al., 2020; Wen et al., 2023).

Hybrid methods attempt to combine the strengths of both by embedding traffic flow theory within data-driven frameworks, using techniques like Physics-Informed Neural Networks (PINNs) to enhance model generalization and interpretability (Fang et al., 2023). Previous fusion methods typically utilized the outputs of fixed-parameter theoretical models as constraints or embedded them into partial differential equations. However, these strategies either introduced uncorrected biases or imposed weak physical constraints, resulting in discrepancies with real-world observations. To address these issues, researchers have increasingly employed neural networks to directly mine physical models or extract heterogeneous, driver-specific parameters. Nevertheless, these approaches focus excessively on instantaneous states and lack temporal memory mechanisms, rendering them unable to predict trajectory fluctuations induced by the inherent uncertainty of human behavior. Consequently, although previous studies have laid a foundation for understanding and predicting traffic oscillations, inherent limitations persist, and precise real-time prediction remains elusive (Mo et al., 2021; Fang et al., 2023; Hao et al., 2025).

Additionally, platoon behavior dominated by HDV exhibits high levels of uncertainty and uncontrollability. Past research has primarily focused on scenarios with 100% penetration rate of ICVs, with limited attention to oscillation propagations in mixed traffic with low-penetration rate of ICVs. Moreover, studies on traffic oscillation propagations in mixed traffic flows with low penetration of ICVs often assume that oscillation transmission is homogeneous and consistent. They tend to overlook the effects of heterogeneous and uncertain behavior of HDVs on oscillation propagation. This assumption significantly diverges from real-world conditions (Gao et al., 2024).

To address these challenges, this study develops a hybrid deep learning model for vehicle platoon trajectory prediction under traffic oscillations. Named the Causal Physics-Informed Deep Learning Model (CPIDLM), it accounts for individual driver behavior variations in platoon modeling. Specifically, we develop a causality-driven network to learn each driver's behavioral parameters within the platoon, complemented by a gating mechanism that dynamically balances physical and data-driven contributions based on real-time traffic conditions. The approach involves utilizing roadside sensing to predict the propagation of traffic oscillations within a mixed traffic flow. This scenario is characterized by a low penetration rate of ICVs, where each ICV is preceded by a random number of HDVs. The primary contributions of this study are as follows:

(1) This study constructs a novel Causal Graph Attention mechanism to explicitly decipher driver behavioral heterogeneity and uncertainty. By disentangling the complex spatial-temporal causal dependencies within vehicle platoons, this approach resolves the interpretability issues of existing models and accurately models the causal impact of adjacent vehicles on trajectory propagation.

(2) We formulate a physics-informed deep learning architecture that enforces kinematic consistency via a newly devised dynamic calibration mechanism. This module orchestrates the interplay between physical priors and data-driven patterns, adaptively balancing their contributions to guarantee prediction robustness and physical validity under stochastic traffic oscillations.

The remainder of this paper is organized as follows. Section 2 reviews existing research on traffic oscillation prediction and platoon dynamics modeling. Section 3 presents the problem formulation and introduces the proposed CPIDLM model. Section 4 presents the experimental data used to rigorously validate the method proposed in this study. In Section 5, real-world trajectory data is employed to train and evaluate the model, demonstrating its effectiveness in capturing platoon dynamics and predicting traffic oscillations. Section 6 concludes the paper and outlines directions for future work.

2 Literature review

2.1. Classical methods for vehicle platoon trajectory prediction

Traffic oscillations, characterized by the nonlinear amplification of disturbances propagating upstream, induce significant flow instability and are heavily influenced by vehicle heterogeneity (Ngoduy et al., 2015; Li et al., 2025; Wu et al., 2025). This non-stationarity causes vehicle kinematic states to undergo instantaneous transitions, rendering future trajectories statistically deviant from historical patterns (Ngoduy et al., 2025). Consequently, prediction models relying solely on single-vehicle historical data ignore spatiotemporal coupling, leading to substantial generalization errors during shock wave evolution.

Existing trajectory prediction methods are predominantly categorized into model-driven and data-driven approaches (Fang et al., 2023). Model-driven approaches, based on microscopic car-following theories (e.g., IDM, Gipps), ensure physical consistency but often enforce deterministic behavioral logic. Despite parameter calibration, they fail to replicate the stochasticity and spontaneous fluctuations inherent in human driving, resulting in trajectories that overly conform to historical trends (Ngoduy et al., 2019; Wen et al., 2023). Conversely, data-driven approaches (e.g., LSTM, GNNs) excel at capturing interaction features (Zhou et al., 2017; Wen et al., 2023). However, they typically neglect oscillation propagation mechanics and suffer from limited interpretability and poor generalization under unstable or sparse data conditions (Hao et al., 2025).

2.2. Physics-Informed Neural Networks for Platoon Trajectory Prediction

To address these limitations, Physics-Informed Neural Networks (PINNs) have emerged as a robust solution by integrating physical laws into deep learning frameworks. As summarized in Table 1, current PINN-based strategies generally fall into three categories: (1) residual prediction, (2) physical loss constraints, and (3) intrinsic model embedding. Furthermore, some researchers have employed deep learning frameworks to construct car-following models or utilized Bayesian methods to develop models with stochastic parameterization to account for driving heterogeneity (Li et al., 2025; Wang et al., 2025). However, these two approaches are primarily designed for the reconstitution of heterogeneous behaviors within car-following simulations; they are not inherently optimized for the real-time, multi-step trajectory prediction of multiple vehicles across extended temporal horizons.

While residual prediction offers marginal gains due to weak constraints, the strategy of physical loss constraints (e.g., PIDL-CF by Mo et al., 2021; Transformer-IDM by Geng et al., 2023) has shown promise (Long et al., 2025). However, these methods often treat physical parameters (e.g., desired time headway) as global constants or derive them via global calibration. This forces the network to approximate an "average driver," creating a fundamental "data-physics conflict" when modeling heterogeneous behaviors: the fixed-parameter physical loss penalizes deviations caused by aggressive or timid driving, coercing predictions to regress toward the mean.

The third strategy, intrinsic model embedding (Hao et al., 2025), mitigates this bias but often dilutes the regulatory influence of physical constraints within deep architectures. Recent attempts utilizing Large Language Models (LLMs) for knowledge distillation (Wang et al., 2025) lack specialized memory mechanisms for complex temporal dependencies and tend to over-smooth essential stochastic fluctuations. Therefore, developing a hybrid fusion methodology that balances physical consistency with heterogeneous stochasticity remains a critical gap. Fig. 2 illustrates the proposed framework designed to address these challenges.

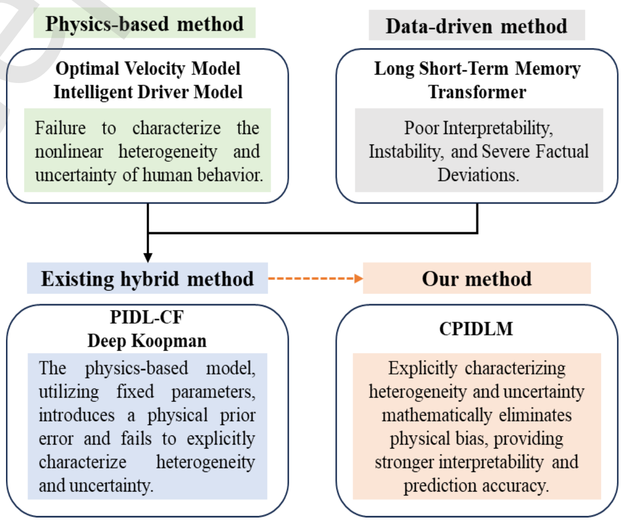


Fig. 2. Current gap in vehicle platoon trajectory prediction

3 Methodology

3.1. Problem statement

This study focuses on predicting the formation and propagation of traffic oscillations within vehicle platoons traveling in the same lane under mixed traffic conditions with low penetration of ICVs. The core assumption is that, for any ICV within the platoon, there are at least two HDVs ahead, forming a mixed platoon. As illustrated in Fig. 3, when the (N-4) th HDV decelerates downstream, the subsequent behavior of the following HDV N-3 through N-1 (all HDVs) is predicted. This allows for accurate identification of traffic oscillation propagation and provides critical information for decision-making of the Nth vehicle, which is an ICV. Accurately forecasting traffic oscillation propagation in mixed traffic with low ICV penetration is essential for enabling stable and energy-efficient control of ICVs under such conditions. This problem can be formalized as follows: consider a vehicle platoon consisting of L vehicles (L > 3), where each ICV has at least two HDVs ahead. Note that if only one HDV is ahead, the platoon does not meet the HDV composition criteria. The lead vehicle is designated Vehicle 1, and the last vehicle is Vehicle L. When any HDV vehicle n ahead of an ICV exhibits unstable behavior such as sudden deceleration or acceleration, the car-following behavior of each vehicle in the platoon is modeled to predict the propagation of traffic oscillations. Formally, the problem can be expressed as follows:

$$X_n(t:t+F) = f_1(X_n(t-P:t)) \tag{1}$$

$$\gamma_{L:n-1}(t:t+\Delta t) \leftarrow g(X_{L:n-1}(t-P:t), X_n) \tag{2}$$

$$X_{L:n-1}(t:t+F) = f_{\gamma_{L:n-1}}\left(X_{L:n-1}(t-P:t), X_n(t:t+F)\right) \tag{3}$$

where $X_n(t-P:t)$ denotes the historical trajectory of the n-th vehicle, which exhibits unstable driving behavior, over the time interval from $t-P$ to the current time t. The function $f_1(\cdot)$ maps this trajectory to a predicted future path $X_n(t:t+F)$ from time t to $t+F$. The past trajectories from vehicle L to $n-1$, over the same period are represented by $X_{L:n-1}(t-P:t)$. A separate function $g(\cdot)$ is used to learn and model the dynamic parameters $\gamma_{L:n-1}(t:t+F)$ that characterize the heterogeneity and uncertainty of these vehicles' following behavior. Based on these parameters, a dynamic model $f_{\gamma_{L:n-1}}(\cdot)$ is constructed to predict the future trajectories $X_{L:n-1}(t:t+F)$ of vehicles L to $n-1$.

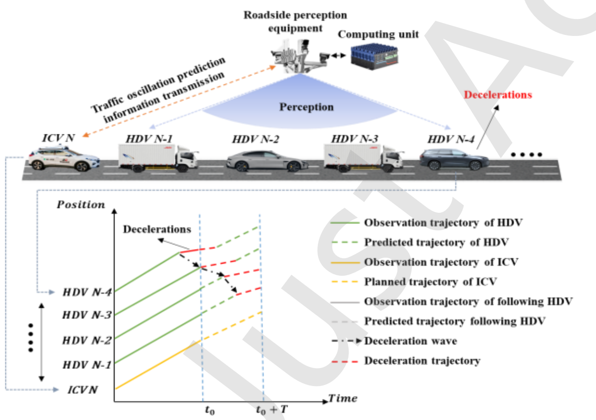


Fig. 3. Method for predicting traffic oscillation propagation based on platoon trajectory forecasting

3.2 Our methodological contributions

This research focuses on the precise trajectory prediction of heterogeneous and uncertain behaviors within mixed platoons under oscillatory scenarios. Specifically, Section 3.4 designs a module for the real-time modeling of individual driver heterogeneity and multi-step behavioral uncertainty. To ensure kinematic feasibility, Section 3.5 incorporates a physics-based module to prevent trajectories from violating physical constraints. Subsequently, Section 3.6 employs a data-driven module to enhance the model's generalization capability. Finally, Section 3.7 introduces a mechanism to achieve a dynamic equilibrium between physical laws and data-driven contributions, ensuring both robustness and accuracy.

3.3 Network structure of CPIDLM

The CPIDLM network architecture is illustrated in Fig. 4. The architecture consists of four modules labeled (a) through (d). (a) The driver heterogeneity and uncertainty feature learning module extracts causal behavioral features based on a causal graph of driver behavior, enabling effective modeling of driver heterogeneity and uncertainty. This module explicitly expresses these variations through five IDM parameters that vary with traffic conditions and time. The parameters output to characterize driver heterogeneity can be directly applied to vehicle platoon dynamics modeling and simulation. (b) The physical module uses these five parameters to compute physical predictions of driver behavior according to the IDM's computational graph. (c) The data-driven vehicle motion feature learning module builds vehicle following behavior characteristics solely from large-scale vehicle platoon data to predict vehicle trajectories purely from data. (d) The adaptive weight module dynamically outputs gating thresholds based on each vehicle's state to integrate the physical predictions with those from the data-driven module. The key advantage of this framework is that the predictions are constrained by physical prior formulas, ensuring consistency with physical realities and producing more reliable and stable results.

3.4 Driver heterogeneity and uncertainty feature learning module

The module for learning drivers' heterogeneity and uncertainty features comprises two parts: the Structural Agnostic Model (SAM) for causal discovery, and the Causal Graph Attention Network combined with LSTM (CGAT-LSTM). The SAM component identifies causal relationships within input data, constructing a causal behavior graph. The CGAT-LSTM model integrates causal relationships with time-series data to predict multi-step dynamic parameters for drivers. This framework characterizes behavioral heterogeneity through inter-driver parameter variations, while quantifying behavioral uncertainty based on the temporal fluctuations within an individual driver's parameters. The CGAT-LSTM layer learns dependencies between features by calculating relationships in accordance with the causal graph and feeds these into the LSTM. The LSTM captures the temporal dependencies of drivers' behaviors. The strength of the model lies in its integration of graph convolutional networks for spatial relationship modeling with LSTM for temporal sequence modeling, enabling effective handling of the complexities involved in learning and representing driving behavior features. The core strength of the model lies in combining the efficient spatial relationship modeling of graph convolutional networks with the deep temporal sequence capturing of LSTM. This fusion enables effective extraction of driver heterogeneity and

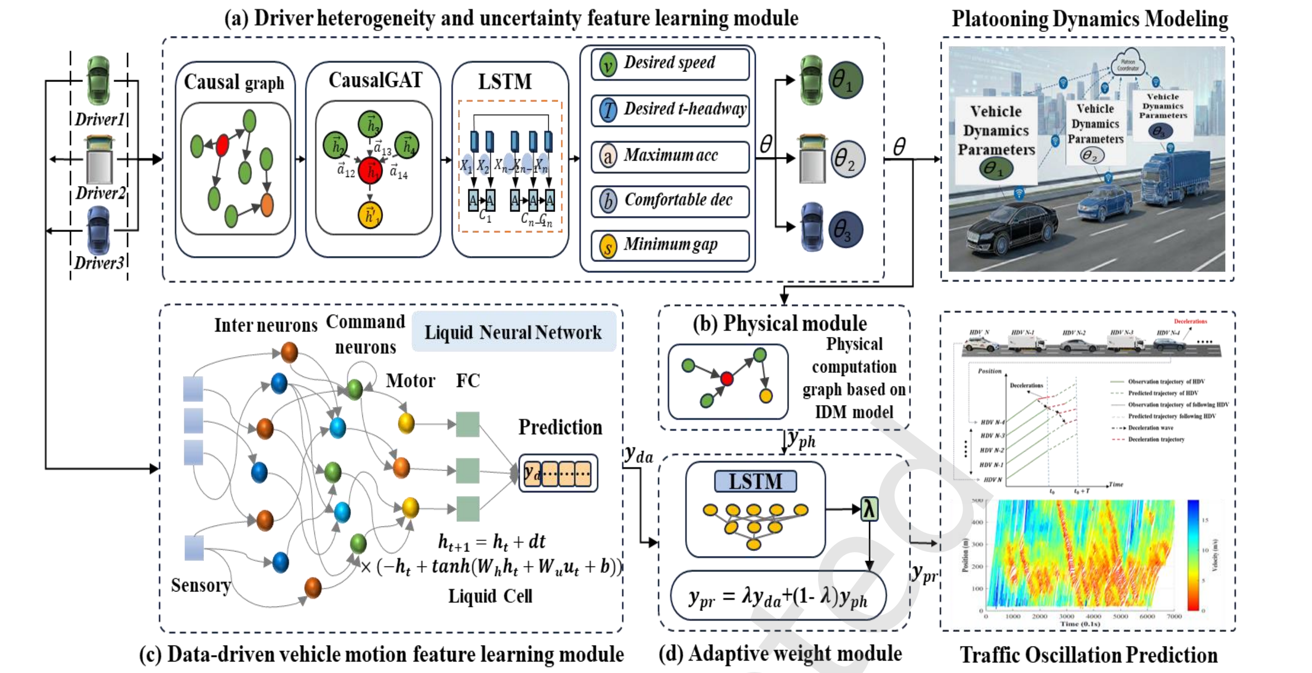


Fig. 4. The framework of the CPIDLM model

uncertainty features, as well as the complex interactions between vehicles. The combined architecture of the SAM module and CGAT is illustrated in Fig. 5. Details of their functionality are given below.

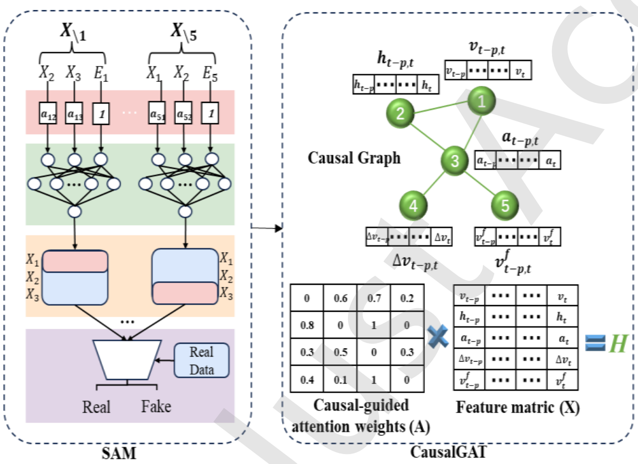


Fig. 5. The SAM model with CGAT combinatorial structure

3.4.1 SAM Module

SAM serves as a causal discovery tool designed to uncover how various traffic conditions influence changes in drivers' car-following behaviors (Kalainathan et al., 2022). It analyzes indicators such as the leading vehicle's speed, the subject vehicle's speed, the speed difference with the leading vehicle, the gap to the leading vehicle, and the subject vehicle's acceleration to identify causal links. Acceleration is used to represent behavioral changes, while other variables collectively define the traffic state. This causal insight provides foundational prior knowledge for the subsequent CGAT-LSTM module to model driver heterogeneity and uncertainty under differing traffic conditions.

Let X_1, X_2, $\cdots$, X_n be input variables. SAM initially models each variable X_i as a function of all other variables X_{-i} (i.e., all variables except X_i), using a flexible model capable of capturing non-linear dependencies:

$$X_i = f_i(X_{-i}, \epsilon_i) \tag{4}$$

where f_i is a flexible, potentially nonlinear function represented by a neural network, and ϵ_i is an independent noise component assumed to capture exogenous randomness in X_i.

The loss function minimized by SAM combines two terms: a reconstruction error measuring the fidelity of each function f_i in predicting X_i, and a regularization term promoting independence of residuals via the discriminator feedback. Formally, the objective can be written as:

$$\mathcal{L}(\{f_i\}_{i=1}^{n}) = \sum_{i=1}^{n} \mathbb{E}[(X_i - f_i(\mathbf{X}_{-i}))^2] + \lambda \sum_{i=1}^{n} \mathcal{I}(\epsilon_i; \mathbf{X}_{-i}) \tag{5}$$

where $\mathcal{L}(\cdot)$ measures the dependence which is approximated adversarially between residuals and input variables, and λ is a hyperparameter balancing the trade-off between fitting accuracy and causal structure sparsity.

The causal adjacency matrix $\widehat{W} \in \mathbb{R}^{n\times n}$ is derived from the trained weight parameters associated with each function f_i, specifically from the learned filters on input features which represent the presence or absence of causal influence. To reduce variability, the final estimate is obtained by averaging the adjacency matrices over multiple independent training runs:

$$\widehat{W} = \lim_{r\to\infty} \frac{1}{r} \sum_{k=1}^{r} \left|W^{(k)}\right| \tag{6}$$

where $W^{(k)}$ denotes the adjacency estimate from the k-th training run.

3.4.2 CGAT-LSTM

During car-following, drivers modify their behavior according to traffic conditions while integrating personal tendencies such as risk perception, driving style, and habits. This leads to individual variability and temporal uncertainty in their following behavior. Consequently, driver heterogeneity results in variations in model parameters across different individuals. Furthermore, the uncertainty inherent in driving behavior causes the parameters of a single driver to exhibit time-varying fluctuations rather than remaining constant. For example, a driver's reaction time changes in response to variations in both vehicle speed and time.

To model and predict these behaviors accurately, we propose a combined CGAT-LSTM model. The CGAT component captures the causal graph topology between traffic states and driver behavior, while the LSTM learns temporal patterns in behavior. Ultimately, the data-driven model processes historical data segments and outputs physical parameters representing the driver's future behavior in real time. This method represents a novel deep learning-based approach for modeling driver behavior parameters, as proposed in this study. The CGAT learns relationships between features by propagating information from each node to its neighbors based on the causal graph. To ensure that causal influences between variables guide the feature extraction in the graph attention network, we introduce causal weights as a modulation term in the attention score calculation. After computing the baseline attention score e_{ij}^{base}, the weighted causal matrix A_{ij}, scaled by a factor β, is added to e_{ij}^{base}. This approach increases the attention scores between nodes with strong causal relationships, biasing the model to assign higher attention weights after applying softmax.

The output of each CGAT layer is defined by the following formula:

$$\alpha_{ij} = \frac{\exp\left(\mathrm{LeakyReLU}\left(\mathbf{a}^T[\mathbf{Wh}_i||\mathbf{Wh}_j]\right)\right)}{\sum_{k\in\mathcal{N}(i)}\exp\left(\mathrm{LeakyReLU}\left(\mathbf{a}^T[\mathbf{Wh}_i||\mathbf{Wh}_k]\right)\right)} \quad (7)$$

where $\mathbf{h}_i$ and $\mathbf{h}_j$ represent the feature vectors of nodes i and j, respectively. $\mathbf{W}$ is a learnable weight matrix that maps node features to a new feature space. $\mathbf{a}$ is a trainable attention coefficient vector used to measure the relevance between node pairs. LeakyReLU is an activation function with a negative slope, typically set at 0.2. α_{ij} represents the attention score computed by the attention mechanism.

$$a_{ij}^{guided} = \alpha_{ij} + \beta \cdot A_{ij} \quad (8)$$

The guided attention score a_{ij}^{guided} is the final attention value adjusted by causal guidance. Here, β is a learnable scalar parameter, and A_{ij} is the causal matrix. This causal matrix is fixed prior knowledge derived from the output of the SAM module.

$$H = ReLU(\hat{A}XW) \quad (9)$$

where H denotes the output of the graph convolution layer, representing the updated feature vectors for each node. $\hat{A}$ is the normalized adjacency matrix. X is the input feature matrix containing the features of each node. W is the learnable weight matrix. $ReLU$ is the activation function applied to introduce nonlinearity in the output.

The output from the graph convolution layer is fed into the LSTM to capture the temporal characteristics of traffic sequence data and the temporal uncertainty of drivers' behaviors. The LSTM aims to model dynamic changes by leveraging temporal dependencies in the time series data.

3.5 Physical module

Prior research is characterized by two primary limitations: first, the reliance on "one-size-fits-all" fixed parameters, which neglects inter-driver heterogeneity; second, even when parameters are tailored to specific drivers, their static nature fails to capture the behavioral uncertainty inherent in traffic oscillations (Wang et al., 2025; Wu et al., 2025). This dual neglect of both diversity and dynamics is the fundamental cause of degraded predictive accuracy in existing models. Relying directly on fixed parameters as physical constraints introduces substantial prediction errors. The simplistic integration of fixed IDM parameters as constraints in deep learning models significantly limits overall model performance.

To address this issue, we propose the following approach. As shown in Fig. 6, vehicle historical time-series data and the causal graph are first input into the CGAT-LSTM network to predict five behavioral parameters of the driver at future time *t~t+F*. Next, the vehicle state at time *t* is fed into the IDM physical model to predict the vehicle's acceleration at *t+1*. This process is iterated continuously to calculate acceleration, speed, and position from time t through *t+F*.

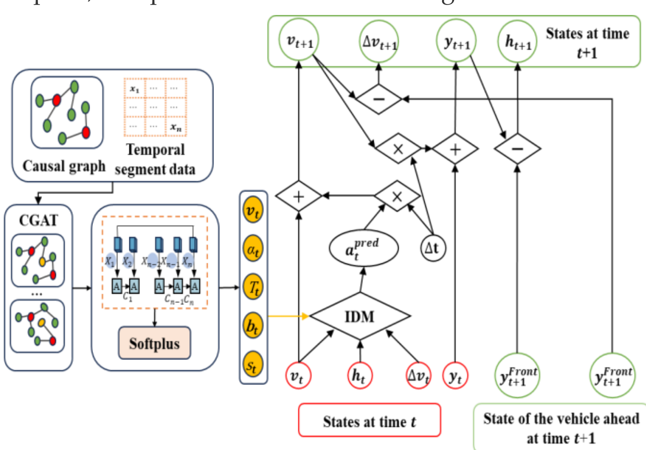


Fig. 6. The Physics-based prediction module using IDM

3.6 Data-driven vehicle motion feature learning module

In recent years, numerous researchers have adopted data-driven deep learning approaches for vehicle platoon dynamics modeling. In traffic conditions characterized by continuous and rapid oscillations, vehicle platoon behavior exhibits significant fluctuations. Under such conditions, physics-based models tend to lag in their predictions. While enforcing constraints on model outputs helps maintain reasonable predictions, the rigidity of physics-based models restricts their effectiveness in scenarios with sustained intense oscillations.

To address these issues, we developed a data-driven deep learning module that relies solely on temporal data features to predict future behavior. Compared to traditional recurrent neural networks, Liquid Neural Networks (LNN) define neuron states through differential equations, thus modeling dynamic systems more effectively (Karn et al., 2024). By incorporating a differential equation of the form $-h + \tanh$, LNNs naturally capture smooth dynamic changes, unlike discrete RNNs that depend entirely on matrix multiplications and additions.

At each step, the LiquidCell takes the current input and previous hidden state to compute the next hidden state. The state update formula for any layer's LiquidCell is as follows:

$$\Delta h_t^{(i)} = -h_{t-1}^{(i)} + tanh\left(W_h^{(i)} h_{t-1}^{(i)} + W_u^{(i)} x_t^{(i)} + b^{(i)}\right) \tag{10}$$

$$x_t^{(i)} = \begin{cases} x_t & i = 1, \\ h_t^{(i-1)} & i > 1. \end{cases} \tag{11}$$

$$h_t^{(i)} = h_{t-1}^{(i)} + \Delta t \Delta h_t^{(i)} \tag{12}$$

where, i denotes the layer number, $W_u^{(i)}$ is the input-to-hidden weight matrix, and $W_h^{(i)}$ is the hidden-to-hidden weight matrix. The input vector at the current time step is $x_t^{(i)}$, which corresponds to the raw features for the first layer and the previous layer's hidden state for subsequent layers. The bias vector is $b^{(i)}$, while $h_t^{(i)}$ represents the updated hidden state. The variable Δt indicates the time step size.

3.7 Adaptive weight module

Past studies combined outputs from physical and data-driven models by optimizing a calibration parameter k as shown in Equation (13). However, this approach overlooks the varying predictive capabilities of both models under different traffic conditions. A fixed k cannot adapt dynamically to changing traffic states. To address this limitation, we propose using a simple neural network that dynamically selects the optimal k value based on the historical performance of each model across different traffic scenarios. In this design, the value of k is not fixed but is dynamically generated by an LSTM network based on the current driving state of the vehicle. Notably, to enhance the constraint effect on the physical model's predictions, the k value is restricted to the range between 0 and 0.4 (Geng et al., 2023).

$$y_{pr} = k y_{da} + (1 - k) y_{ph} \tag{13}$$

where y_{pr} denotes the final integrated predictive output, while y_{ph} and y_{da} represent the predictions from the physics-based and data-driven modules, respectively.

4 Data

In recent years, numerous researchers have adopted data-driven deep learning approaches for vehicle platoon dynamics modeling. To systematically validate the effectiveness of the proposed method, this study utilizes the NGSIM dataset for experimental verification. Widely studied in transportation research, the NGSIM dataset has become a de facto standard (Geng et al., 2023). While the raw NGSIM dataset is known to contain significant sensor noise and measurement errors, this study utilizes a refined version that has undergone large-scale smoothing and denoising by previous researchers to ensure data fidelity (Montanino and Punzo, 2015). Furthermore, we applied a secondary smoothing process to further eliminate residual outliers and ensure the continuity of vehicle trajectories.

To validate the model's generalization capability, generalization experiments were conducted using the TOD_VT dataset (Wen et al., 2024). The dataset covers 105 hours of footage with multi-camera coordination for wide-area traffic observation in Wuhan, China. This study uses data from the I-80 segment during the periods of 5:00-5:15 pm and 5:15-5:30 pm, which collectively consist of 2,096,000 records from 3,626 vehicles. The trajectory data were smoothed using a Savitzky-Golay filter (Mo et al., 2021). To avoid data contamination, we selected vehicle platoon data with more than two cars from 5:00 to 5:15, including both stable platoon driving and traffic oscillation scenarios. A total of 465 vehicle platoons were selected, generating 333,055 samples with an observation window of 50 steps and a prediction window of 1 step. The data were split into training, validation, and test sets in a 60:20:20 ratio for platoon behavior modeling and prediction. Additionally, from the 5:15 to 5:30 dataset, platoons exhibiting traffic oscillations were identified. The 92 platoons were reserved exclusively for testing and were not included in model training.

5 Results and discussions

5.1 Modeling implementation

5.1.1 Parameter settings and baselines

To evaluate the proposed model's superiority in predicting vehicle platoon behavior under traffic oscillations and to assess the contribution of each module, we designed several comparative models as follows.

(1) Physics-informed model baselines

PL-IDM: This model combines an LSTM with IDM, where input data is fed directly into the LSTM, which outputs the five IDM parameters subsequently used by the IDM model to generate predictions. Its architecture matches the proposed model's Driver heterogeneity and uncertainty module without the CGAT component, serving to validate the impact of the CGAT module.

PT-IDM: Structurally identical to PL-IDM, except the LSTM is replaced with a Transformer model.

PN-IDM: Also identical in structure to PL-IDM, with the LSTM replaced by an LNN model.

PIT-IDM (Geng et al., 2023): This represents a state-of-the-art hybrid model combining Transformer and IDM for trajectory prediction. The IDM model uses fixed parameters to produce physical predictions. The Transformer's loss function incorporates the error between its predictions and the IDM's outputs, guiding the Transformer's learning. Since it employs fixed IDM parameters without accounting for driver heterogeneity and uncertainty, this introduces inherent bias and limits its predictive performance. PIT-IDM is a state-of-the-art trajectory prediction model that integrates data-driven and physics-based approaches.

PIL-IDM (Mo et al., 2021): Architecturally identical to PIT-IDM, but replaces the Transformer module with an LSTM.

(2) Data-driven model baselines

LSTM (Zhang et al., 2019): The model takes historical information of both the ego vehicle and the preceding vehicle as input and predicts the future speed of the ego vehicle.

LNN (Karn et al., 2025): Inspired by GNN models, the LNN model in this study enhances prediction accuracy by updating states using Euler integration.

Transformer (Fang et al., 2023): The original Transformer model includes a decoder that produces single-step predictions to forecast vehicle platoon behavior under traffic oscillations. To enable multi-step prediction, this study removes the decoder and modifies the model accordingly while retaining the other components unchanged.

(3) Physics-based model baselines

IDM: This study calibrates IDM model parameters using the DIRECT (Direct Search Method) and SQP (Sequential Quadratic Programming) algorithms (Li et al., 2016). It is important to note that calibration is performed exclusively on the selected training set, with no involvement of other datasets. With velocity set as the calibration objective, the resulting calibrated parameters are: a desired velocity $v_{desired}$ of 16.138, a desired time headway T of 0.502, a maximum acceleration a_{max} of 0.403, a comfortable braking deceleration b_{safe} of 3.883, a minimum gap s_0 of 1.103, and a delta exponent δ of 4.0.

5.1.2 Measures of effectiveness

This study uses Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) to evaluate the models. The formulas are as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(y_i - \bar{y}_i)^2} \tag{14}$$

$$MAPE = \frac{100\%}{N}\sum_{n=1}^{N}\left|\frac{y_i - \bar{y}_i}{y_i}\right| \tag{15}$$

where y_i is the true value, $\bar{y}$ is the predicted value and N is the number of samples.

5.2 Comparison of model performance

5.2.1 Ablation study

To validate the rationale and contribution of each module proposed in this study, ablation experiments were conducted using car-following data extracted from the I-80 dataset (5:00 - 5:15 PM), partitioned into training, validation, and test sets with a 60:20:20 ratio. Consistent with existing physical modeling approaches, all models utilized a 5-second historical input window to predict behavior for the subsequent 0.1 seconds. In the experimental design, LSTM served as the baseline; PL-IDM was derived by excluding modules b, c, and d and the CGAT structure from module a to verify the driving behavior parameter learning fusion method; CPL-IDM represented the complete module a to assess the CGAT structure; CPT-IDM represents replacing the LSTM in CPL-IDM with a Transformer; CPL-IDM-R and CPL-IDM-P represent causal matrices derived from SAM mining, where random matrices and permuted matrices are substituted respectively; CPIDLM-T and CPIDLM-L replaced module c with a Transformer and LSTM, respectively, to validate the choice of module c; and CPIDLM-A replaced the dynamic weight fusion in module d with an optimized fixed-weight approach. The results in Table 1 show that PL-IDM reduced the velocity error from 0.155 (baseline) to 0.135, demonstrating the effectiveness of the proposed parameter prediction method, while CPL-IDM further reduced the error to 0.13, confirming that the CGAT structure enhances the modeling of driver behavior heterogeneity. Furthermore, the higher errors observed in CPIDLM-T and CPIDLM-L justify the selection of the LNN, and the significant increase in error for CPIDLM-A (from 0.129 to 0.134) highlights the limitations of traditional fixed weights, thereby validating the effectiveness of the proposed dynamic weight fusion method.

Table 1. Comparison of Car-Following Behavior Modeling Errors

Model	Velocity RMSE (m/s)	Gap RMSE (m)	Velocity MAPE (%)	Gap MAPE (%)
LSTM	0.155	0.061	0.729	0.055
PL-IDM	0.135	0.053	0.503	0.047
CPL-IDM	0.131	0.051	0.495	0.046
CPT-IDM	0.132	0.051	0.499	0.047
CPL-IDM-R	0.172	0.085	0.887	0.061
CPL-IDM-P	0.163	0.069	0.781	0.059
CPIDLM -T	0.132	0.052	0.446	0.047
CPIDLM -L	0.131	0.051	0.495	0.046
CPIDLM -A	0.134	0.053	0.484	0.048
CPIDLM	**0.129**	**0.050**	**0.425**	**0.045**

5.2.2 Modeling results of driver heterogeneity and uncertainty in vehicle platoons

This study employs the CGAT-LSTM module to model platoon behavior, generating five IDM parameters for each driver to quantitatively capture driver heterogeneity and uncertainty. The collective set of these parameters for all vehicles constitutes the platoon behavior model. The car-following behavior data is split into training, validation, and test sets in an 60:20:20 ratio. As shown in Fig. 7, the causal relationship diagram extracted by the SAM module is presented. The Pvs is the speed of the preceding vehicle, Fvs is the speed of the following vehicle, Fva is the acceleration of the following vehicle, Dpv is the distance to the preceding vehicle, and Spv is the speed difference of the preceding vehicle. The thickness of the lines in the diagram represents the strength of the influence. The red values in the diagram indicate the degree of influence. For instance, Fvs is most significantly affected by Dpv.

From the diagram, it is clear that the influence relationships among different features vary significantly. The speed of the following vehicle is primarily affected by the preceding vehicle's speed and the distance to the preceding vehicle. The acceleration of the following vehicle is mainly influenced by the following distance and the speed difference between the own vehicle and the preceding vehicle. This aligns with human driving behavior, where drivers adjust their following behavior based on the following distance and speed difference with the preceding vehicle. The causal behavior diagram output by the SAM module injects prior knowledge into the subsequent graph neural network structure, significantly enhancing both model performance and interpretability.

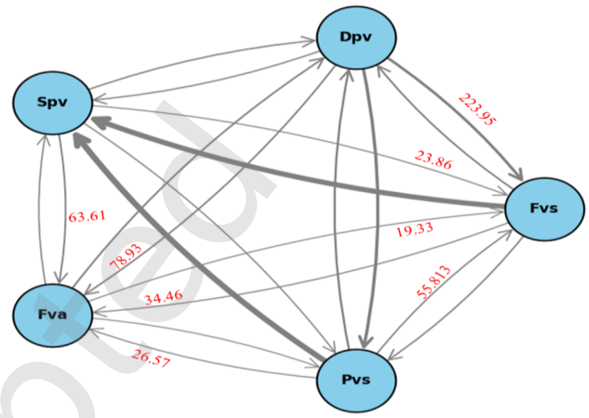


Fig. 7. Causal behavior graph of car-following behavior

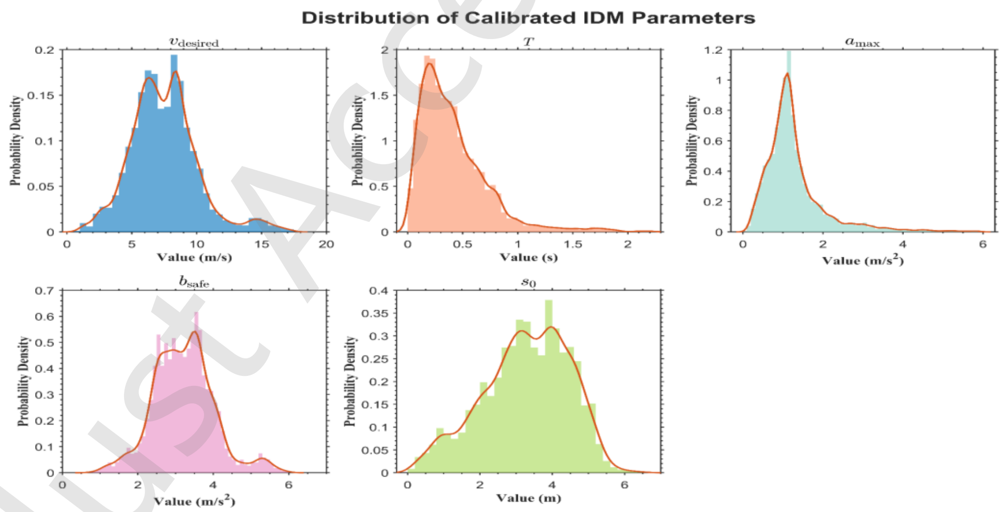


Fig .8. CGAT-LSTM module parameter learning results

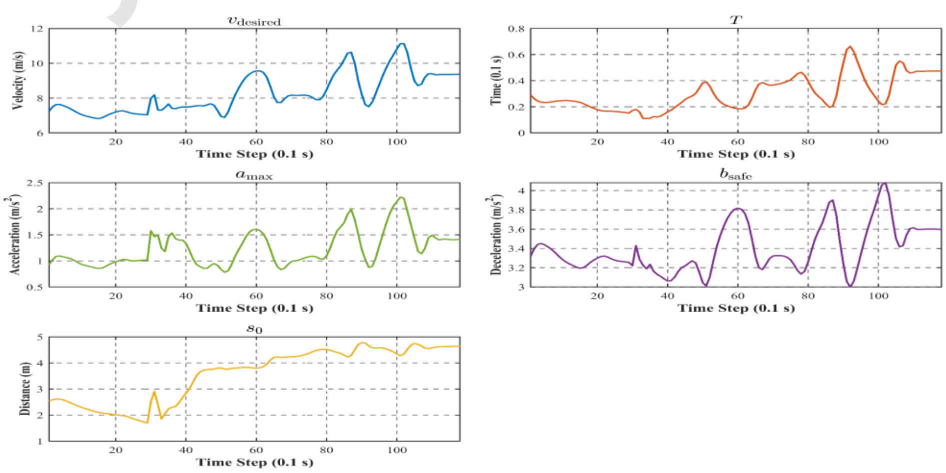


Fig. 9. The Parameter variations of a driver over a continuous time period

Fig. 8. illustrates the CGAT-LSTM module's output, showing the modeled heterogeneity and uncertainty for all drivers in the test set. The $v_{desired}$ is desired velocity,T is desired time headway, a_{max} is maximum acceleration, b_{safe} is comfortable braking deceleration, s_0 is minimum gap s_0. The figure reveals that the five parameters vary within a certain range rather than remaining fixed for different drivers. This variation reflects differences in individual driving styles. Furthermore, as shown in Fig. 9, we analyzed the parameter outputs for a single driver at each time point and observed subtle fluctuations in the five parameters. These variations arise from the inherent uncertainty of driver behavior. To further evaluate the advantages of the proposed method in modeling behavioral heterogeneity and uncertainty, a simulation experiment was conducted. The lead vehicle follows trajectories from real-world datasets, whereas each follower is initialized with its respective historical car-following data before transitioning to iterative model predictions.

Fig. 10. illustrates the results for an 8-vehicle platoon (Leader Vehicle ID: 64) from the I-80 dataset. It is evident that the traditional IDM produces overly idealized simulations, failing to capture the heterogeneity of car-following behaviors and the nonlinear propagation characteristics of traffic oscillations. Similarly, traditional data-driven methods (LSTM, LNN, Transformer) struggle to effectively reproduce behavioral heterogeneity, resulting in highly uniform trajectories. While recent hybrid methods (PIL-IDM, PIT-IDM) capture heterogeneity to some extent, they exhibit significant deviations from the actual trajectories. In contrast, the method proposed in this study achieves the optimal performance in the platoon simulation, accurately reproducing both driver heterogeneity and the actual vehicle trajectories.

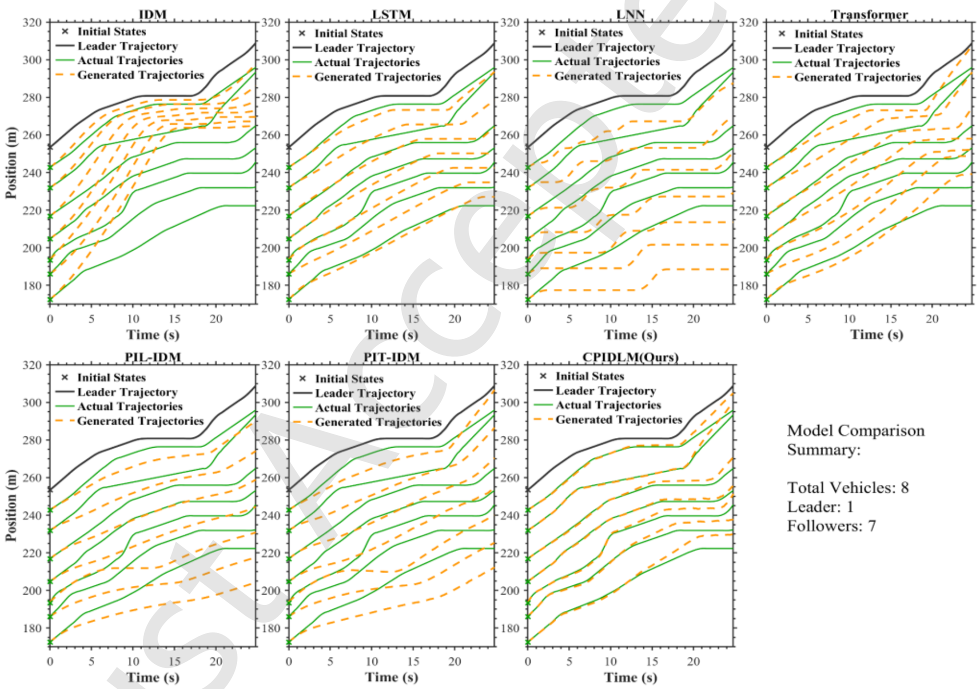


Fig. 10. Comparison of vehicle platoon behavior modeling results

5.2.3 Comparison of platoon trajectory prediction performance in traffic oscillation

Recursive rollout of followers' states based on the leader's direct multi-step trajectory as a boundary. The accurate prediction of traffic oscillation propagation depends on the precise forecasting of the multi-step future behaviors of each vehicle in the platoon. Fig. 11 presents the RMSE and MAPE values for velocity errors across prediction horizons ranging from 5 to 30 steps. In the image, "ours" refers to the CPIDLM model. As indicated by the figure, the proposed model achieves optimal performance in multi-step prediction. Table 2 summarize RMSE error metrics from 5 to 50 steps predictions, with the best results highlighted in bold. Our model consistently achieves superior accuracy in both speed and gap predictions, with Gap forecasts notably excelling in all scenarios. Compared with the state-of-the-art models PIL-IDM and PIT-IDM, our proposed complete model CPIDLM achieves an average reduction of 4% in velocity prediction error and 14% in gap error.

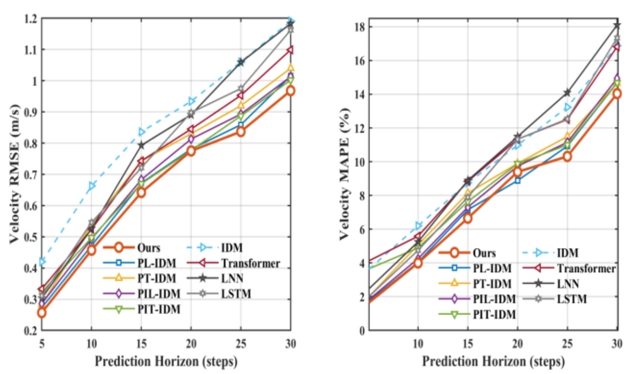
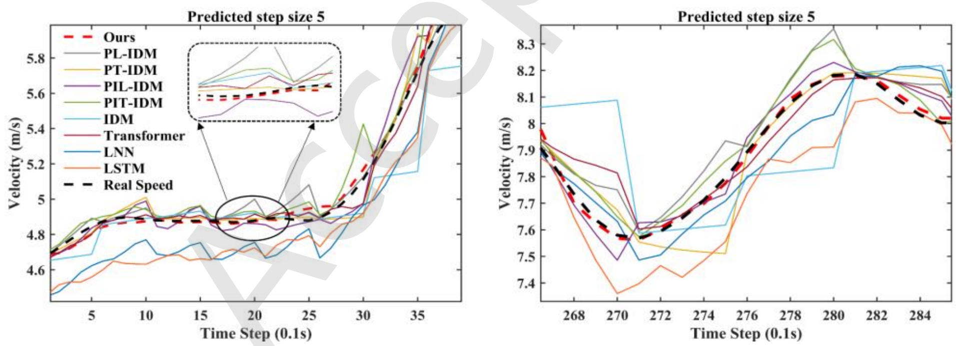


Fig. 11. Comparison of multi-step velocity prediction errors

Compared to the state-of-the-art models PIL-IDM and PIT-IDM, our proposed complete model CPIDLM reduces the 50-step speed prediction error by an average of 15% and the gap error by 20%. Compared to existing models, the average gap prediction error (RMSE) decreases by 16%.

Table 2. Comparison of multi-step prediction error RMSE for platoon behavior

Model	Velocity RMSE (m/s)							Gap RMSE (m)						
	5	10	15	20	25	30	50	5	10	15	20	25	30	50
CPIDLM[ours]	**0.257**	**0.457**	**0.642**	**0.775**	**0.837**	**0.968**	**1.312**	**0.126**	**0.851**	**1.416**	**1.717**	**2.118**	**2.612**	**3.981**
PL-IDM[ours]	0.273	0.472	0.672	0.781	0.859	1.015	1.436	0.131	0.926	1.480	1.765	2.216	2.686	4.355
PT-IDM[ours]	0.283	0.539	0.743	0.830	0.920	1.040	1.495	0.131	0.923	1.481	1.769	2.198	2.705	4.710
PIL-IDM	0.286	0.493	0.683	0.813	0.893	1.013	1.567	0.231	1.012	1.655	1.978	2.221	2.827	4.951
PIT-IDM	0.323	0.497	0.670	0.777	0.887	1.002	1.541	0.233	1.027	1.675	1.986	2.333	2.829	5.116
IDM	0.420	0.663	0.836	0.934	1.060	1.191	2.051	0.233	1.091	1.658	1.997	2.357	2.876	5.310
Transformer	0.333	0.524	0.743	0.845	0.953	1.099	1.757	0.35	1.112	1.499	1.959	2.329	2.865	5.166
LNN	0.303	0.526	0.793	0.891	1.059	1.183	1.876	0.342	1.011	1.677	1.959	2.306	2.851	5.361
LSTM	0.311	0.546	0.721	0.898	0.975	1.162	1.773	0.238	1.012	1.687	1.946	2.307	2.835	5.337



(a) Constant speed to accelerating (b) Unstable variable-speed

Fig. 12. Comparison of model prediction performance under steady and varying speeds

Fig. 12 illustrates prediction results for both stable uniform-to-acceleration car-following and unstable car-following under traffic oscillations at a five-step horizon. In Fig. 12(a), other models exhibit minor unstable fluctuations during uniform speed following and larger deviations during sustained acceleration. Conversely, our proposed model CPIDLM closely aligns with the ground truth in both stable and accelerating scenarios, demonstrating precise dynamic modeling of platoon behavior. Moreover, under traffic oscillation conditions, vehicle speeds fluctuate sharply within short time intervals, posing a stringent test for nonlinear dynamic modeling. As shown in Fig. 12(b), our model maintains exceptional prediction accuracy in these oscillatory scenarios, whereas other models exhibit significant errors. This highlights the strong nonlinear modeling capacity of our approach, driven by the parameter learning module's ability to capture driver heterogeneity and uncertainty, coupled with the gating module's dynamic adaptation to operating conditions.

The 92 selected vehicle platoons which generate traffic oscillations were used entirely as a test set to evaluate each model's capability in modeling and predicting platoon behavior under traffic oscillations. It is noteworthy that all 92 platoon data samples originate from a new time period. Detailed prediction errors of traffic oscillation propagation in the platoon for each model are shown in Table 3. Compared to the optimal model PIT-IDM, CPIDLM reduces the velocity prediction error (RMSE) by 12.1% and the gap prediction error (RMSE) by 25.5%. Our proposed model

Table 3. Comparison of multi-step prediction error for platoon behavior

Model	Velocity RMSE (m/s)	Gap RMSE (m)	Velocity MAPE (%)	GAP MAPE (%)
CPIDLM[ours]	**0.72**	**2.01**	**15.48**	**20.72**
PL-IDM[ours]	0.76	2.11	16.06	21.75
PT-IDM[ours]	0.79	2.12	15.66	21.86
PIL-IDM	0.82	2.71	17.82	27.94
PIT-IDM	0.82	2.70	15.73	27.84
IDM	0.88	2.78	16.68	28.66
Transformer	0.83	2.72	18.07	28.04
LNN	0.86	2.75	19.02	28.08
LSTM	0.85	2.78	19.15	28.61

outperforms all others and demonstrates superior generalizability. This confirms that integrating physical prior models reduces the deep learning models' reliance on data.

To further demonstrate the capability of our model in predicting vehicle platoon behavior under traffic oscillations, Fig. 13 presents comparative results. The proposed CPIDLM model delivers the best prediction accuracy in oscillatory traffic conditions. Unlike other models, CPIDLM does not exhibit a sharp increase in

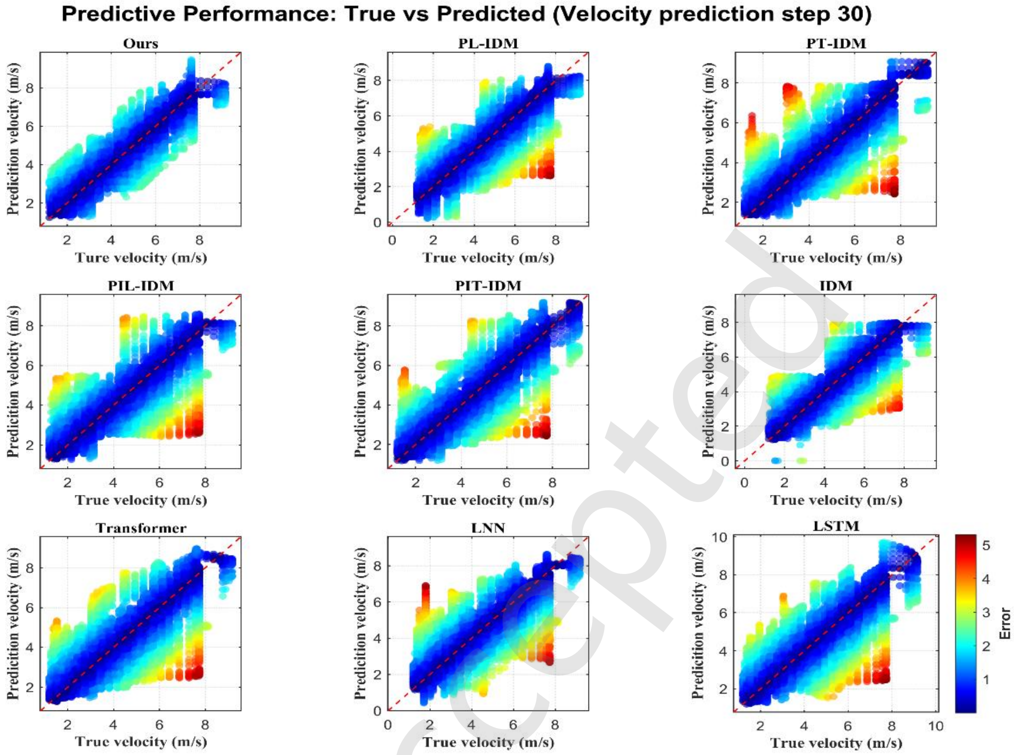


Fig. 13. Comparison of 30-step platoon behavior prediction results at different speeds under traffic oscillations

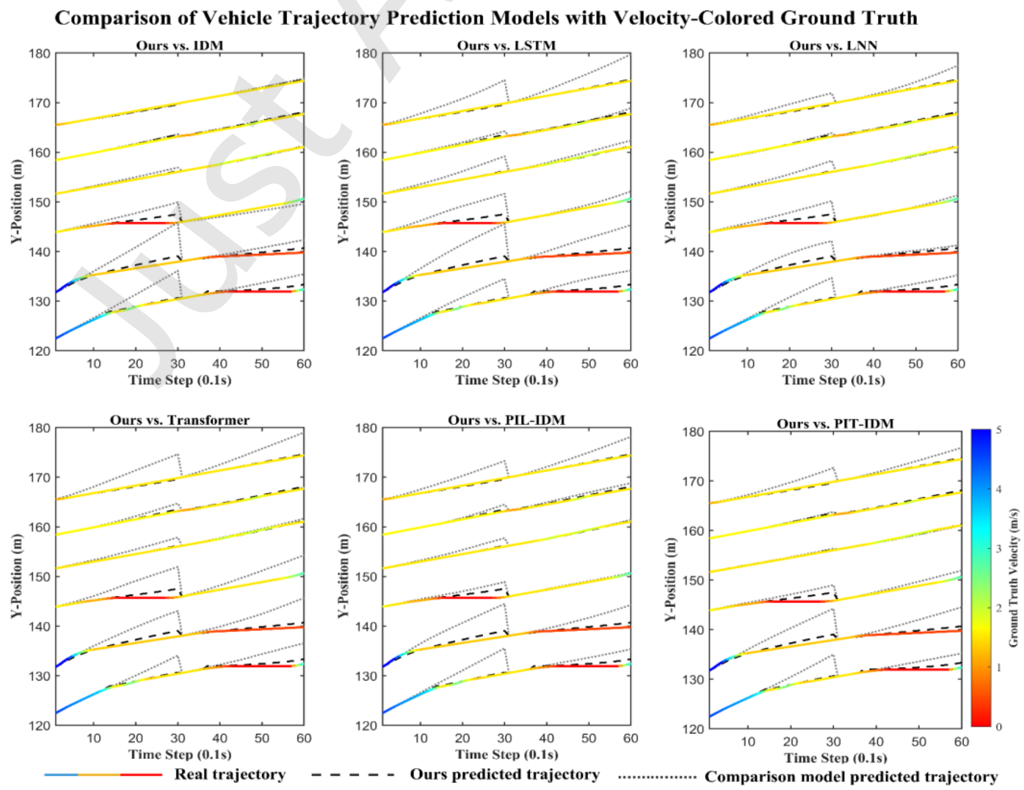


Fig. 14. Comparison of car-following trajectory predictions in platoons under traffic oscillations

prediction errors when platoon speed rises, avoiding large deviations in predicted values. This advantage stems from the effective modeling of traffic oscillations enabled by the causal behavior learning module and adaptive weight module incorporated in our approach. The causal learning module captures the propagation effects of traffic oscillations within the platoon, while the adaptive weight module dynamically adjusts balancing thresholds based on driving conditions, enhancing the model's predictive ability under traffic oscillations.

Fig. 14 shows the trajectory predictions for a six-vehicle platoon experiencing traffic oscillations. In the image, "ours" refers to the CPIDLM model. After the leading vehicle decelerates and then accelerates, the platoon first experiences a deceleration wave followed by an acceleration wave. To clearly illustrate local details, the figure focuses on the segment from the deceleration wave reaching the fourth vehicle to the acceleration wave reaching the same vehicle. The CPIDLM model again achieves superior predictive accuracy. As the deceleration wave reaches the fourth vehicle, this vehicle slows continuously from 0 to 2 seconds, then begins accelerating. CPIDLM accurately predicts both behaviors. When the deceleration wave propagates from the 4-th to the 5-th vehicle, other models fail to capture the resulting behavioral changes as effectively as CPIDLM. The CPIDLM model accurately predicted the propagation of deceleration waves from the lead vehicle to the last vehicle in the platoon. Overall, CPIDLM provides a complete and precise prediction of traffic oscillation propagation within the platoon.

To assess the generalization capability of the model, 137 vehicle platoons meeting the selection criteria were extracted from lanes 3 and 4 of the TOD_VT dataset and partitioned into training, validation, and test sets in a 60:20:20 ratio. The experiment utilized a model pre-trained on the NGSIM dataset (for 30-step prediction), into which 0%, 50%, and 100% of the TOD_VT training data were respectively incorporated. Performance was then validated using the test set. As shown in Fig. 15, the proposed model maintains optimal prediction performance on the new dataset; regardless of the proportion of new data introduced (from 0% to 100%), the proposed method consistently exhibits the lowest prediction errors. CPIDLM demonstrates superior generalization performance, without exposure to new scenarios during training, it outperforms the leading PIT-IDM model with a 13.6% lower spacing error. Furthermore, with the inclusion of all new scenario data in the training set, CPIDLM maintains the minimum prediction errors for both spacing and velocity, achieving a 9.6% reduction in spacing error compared to PIT-IDM.

6 Conclusion

This study proposed a novel hybrid framework, the CPIDLM designed for high-fidelity traffic oscillation prediction. The CPIDLM uniquely integrated causal graph structures to explicitly capture driver behavior heterogeneity and the causal interactions among vehicles. By embedding prior knowledge from traditional traffic physics models into the deep learning architecture, a adaptive weight module dynamically adjusted the weights between the physical and data-driven components, enhancing the model's adherence to traffic dynamics and improving prediction robustness. The key findings of this study are summarized as follows:

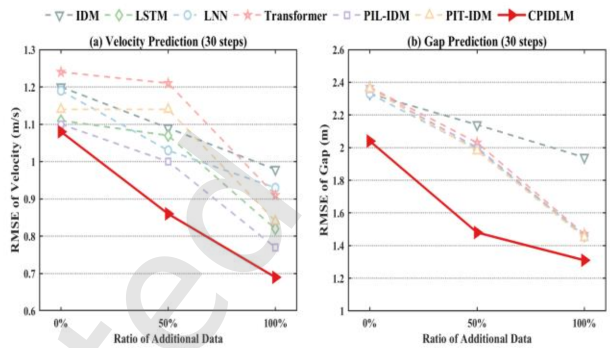


Fig. 15. Experimental results of model generalization on the TOD_VT dataset

(1) The proposed Behavioral Causal Learning module effectively captures the heterogeneity and uncertainty in human driving behavior and the causal relationships between neighboring vehicles, addressing limitations in existing models that struggle to integrate diverse driving behaviors with physical traffic dynamics.

(2) Prior knowledge from classical traffic physics models is seamlessly embedded within the deep learning framework. The adaptive weight module dynamically balances the contributions of the physics-based and data-driven models, thereby reinforcing compliance with traffic dynamic principles and enhancing prediction robustness.

(3) Systematic validation using real-world trajectory datasets demonstrates that the proposed CPIDLM reduces gap prediction error by 16.7% and speed prediction error by 16.1% compared to existing models, showing remarkable superiority in both accuracy and generalization capabilities.

While the current static causal matrix provides a robust structural prior, it may struggle to capture the evolving interaction patterns inherent in non-stationary traffic flow. To address this, subsequent research could explore State-Aware Adaptive Causal Mechanisms. Specifically, integrating regime-switching models or dynamic gating units would allow the causal structure to adaptively reconfigure its edge weights based on real-time traffic conditions. Finally, it is crucial to investigate how predictive information regarding these oscillations can be leveraged to optimize vehicle behavior and string stability under such dynamic conditions.

Author contributions

Jipu Li: Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Shan Tian:** Methodology. **Dong Ngoduy:** Writing – review & editing. **Ye Li:** Software, Data curation, Funding acquisition. **Qijun Huang:** Formal Analysis, Methodology. **Zhongbin Luo**: Methodology. **Shan Fang:** Data curation.

Replication and data sharing

The source codes and replication package are available at https://doi.org/10.26599/ETSD.2026.9190014 and https://github.com/Liangcheng0920/CPIDLM-Vehicle-Platoon-Trajectory-Prediction-Under-Traffic-Oscillation.

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Declaration of competing interest

The author declare that they have no know competing financial interests or personal relationships that could have appeared to have influence on the work reported in this paper.

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