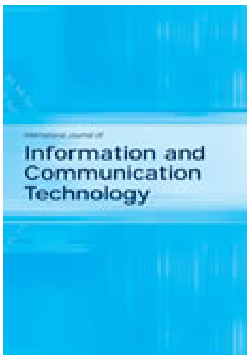


International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Multi-intersection traffic flow prediction control based on vehicle-road collaboration V2X and improved LSTM

Renyong Zhang, Shibiao He, Peng Lu

Article History:

Received:	16 October 2024
Last revised:	31 October 2024
Accepted:	01 November 2024
Published online:	18 December 2024

Multi-intersection traffic flow prediction control based on vehicle-road collaboration V2X and improved LSTM

Renyong Zhang*, Shibiao He and Peng Lu

Information and Communication Technology Research Center,
Chongqing Institute of Engineering,
Chongqing, 400056, China
Email: ryzhang365@163.com
Email: chuntianhuarxq@163.com
Email: 552437915@qq.com
*Corresponding author

Abstract: Traditional multi-intersection traffic flow prediction and control methods often lack real-time and adaptability, and are difficult to cope with complex and changing traffic environments. To solve these two problems, this paper proposes a multi-intersection traffic flow prediction and control method based on vehicle-to-guideway collaboration (V2X) and improved LSTM. Firstly, real-time information interaction between vehicles and roadside devices is achieved through V2X technology. Secondly, an improved LSTM model introducing a sliding time window update mechanism is applied to the collected data to achieve high-precision prediction of traffic flow. Finally, a multi-intersection cooperative adaptive control strategy is designed based on the prediction results. The experimental results show that this method proposed in this paper reduces the average vehicle delay time by 29.0% and improves the road network throughput by 14.6% under high traffic conditions. Meanwhile, the improved LSTM model reduces the computation time from 135 ms to 55 ms.

Keywords: V2X; LSTM; multi-intersection traffic flow prediction; cooperative adaptive control; CAC; intelligent transport system.

Reference to this paper should be made as follows: Zhang, R., He, S. and Lu, P. (2024) 'Multi-intersection traffic flow prediction control based on vehicle-road collaboration V2X and improved LSTM', *Int. J. Information and Communication Technology*, Vol. 25, No. 11, pp.52–68.

Biographical notes: Renyong Zhang received his Master's degree in Shandong University of Technology in 2014. He is currently an Associate Professor at the Chongqing Institute of Technology. His research interests include intelligent transportation and car networking technology.

Shibiao He received his Doctorate from the Chongqing University in 2003. He is currently a Professor at the Chongqing Institute of Technology, and his research direction is wireless communication network.

Peng Lu received his Master's degree from the Chongqing University in 2020. He is currently a Lecturer at the Chongqing Institute of Technology, and his research direction is integrated circuit design.

1 Introduction

In recent years, traffic congestion has become a common challenge faced by large cities around the world, putting forward higher requirements for urban traffic management and planning. Traditional traffic management methods are limited by the lack of real-time data and insufficient responsiveness to complex traffic dynamics, making it difficult to adjust traffic signals in a timely and efficient manner to adapt to changing traffic flows (Arnott and Small, 1994; Barth and Boriboonsomsin, 2009). This problem is particularly prominent in urban road networks with multiple intersections, and there is an urgent need to introduce advanced technological means to improve the accuracy and real-time performance of traffic flow prediction and signal control.

Traffic flow prediction control is a key aspect in intelligent transport systems (De-Palma and Lindsey, 2011; Chow et al., 2014). Traditional methods mainly rely on fixed signal timing and statistically-based prediction models. Al-Khalili (1985) proposed a fixed-time control (FTC) method based on the statistical characteristics of traffic flow, whereby fixed signal periods and phase timings are developed by analysing historical traffic data. Although this method can operate effectively under relatively stable traffic flow, it lacks flexibility and adaptability in the face of dynamic changes in traffic flow. Viloria et al. (2000) proposed a vehicle queue length estimation model to analyse and predict intersection traffic using queuing theory. The model calculates queue lengths and delays at intersections by estimating vehicle arrival and service rates. However, this method assumes that the traffic flow has steady state characteristics and is unable to effectively deal with stochastic and sudden changes in the traffic flow, limiting its usefulness.

With the development of sensor technology and communication technology, adaptive traffic control methods based on real-time data have gradually emerged. Sims and Dobinson (1980) proposed the Sydney Coordinated Adaptive Traffic System (SCATS) system, which adopts a decentralised adaptive control strategy to select the best signal timing scheme according to the real-time changes in traffic flow. The system has been applied in several cities with remarkable results. However, SCATS lacks sufficient flexibility in dealing with abnormal traffic events due to its reliance on historical data, and Hunt (1982) developed the split cycle and offset optimisation technique (SCOOT) system, which dynamically adjusts the signal timing to achieve coordinated control of multiple intersections by acquiring real-time traffic data from roadside detectors. coordinated control of multiple intersections. Although SCOOT improves the traffic efficiency to a certain extent, it depends on the accuracy of the detectors and has a limited response speed in the face of unexpected traffic conditions. Zhao et al. (2024) introduced a multi-intelligence reinforcement learning method, which achieves real-time optimal control of a complex traffic network through the synergy of the intelligences. Experimental results show that this method has advantages in reducing vehicle delays and queue lengths. However, the model requires a large amount of computational resources in the training process and may have the problem of slow convergence in real large-scale networks.

Deep learning models, especially the improved long-short-term memory (LSTM) network, show unique advantages in processing time series and capturing complex nonlinear relationships. Yang et al. (2019) proposed a traffic flow prediction model based on LSTM, which can effectively capture the temporal characteristics of traffic flow and improve the prediction accuracy. However, the model mainly targets a single road section and does not consider the correlation between multiple intersections, which limits its application in complex traffic networks. Wang et al. (2022) developed a traffic gated graph neural network (traffic-GGNN) for multi-intersection traffic flow prediction. The model not only considered the time dependence, but also incorporated the spatial topology of the road network, which significantly improved the prediction performance. However, due to the high model complexity and large computational cost, it is difficult to be applied in real time in practical traffic control.

Existing multi-intersection traffic flow prediction and control methods still have deficiencies, although they have made some progress. Firstly, LSTM-based traffic flow prediction models (Yang et al., 2019) usually target a single road section, and despite the improvement in prediction accuracy, they lack the consideration of road network structure in multi-intersection scenarios, and thus are difficult to effectively capture the complex spatial and temporal correlations among multiple intersections. Secondly, traffic-GGNN (Wang et al., 2022) has made a breakthrough in capturing spatial topological relationships, but the high model complexity and computational cost make it difficult to meet the real-time requirement, which restricts its application in practical traffic control.

In order to solve the above problems, this paper proposes a multi-intersection traffic flow prediction and control method based on vehicle-to-guideway collaboration (V2X) and improved LSTM. Our main innovations and contributions include:

1 To address the lack of real-time in multi-intersection traffic flow prediction, this paper introduces vehicle-road collaboration (V2X) technology.V2X enables real-time information interaction between vehicles and road infrastructure. Using the high-precision traffic flow data acquired by V2X in real time improves the model's ability to perceive dynamic changes in traffic flow. This improvement effectively enhances the model's adaptability in multi-intersection complex traffic networks and achieves high-precision, real-time prediction of multi-intersection traffic flow.

2 Aiming at the problems of high computational complexity and difficult real-time application of traditional LSTM model in multi-intersection traffic flow prediction, this paper proposes an improved LSTM model. By introducing a sliding time window update mechanism, the model is able to continuously learn new data and update the parameters in real time, avoiding an overly complex model structure and reducing the computational cost. At the same time, the ability to learn from historical traffic trends is retained to ensure the accuracy of the prediction. The method significantly improves the computational efficiency while ensuring the model prediction performance, and is more suitable for real-time applications in practical traffic control.

2 Data acquisition and pre-processing

2.1 Traffic flow detection based on LiDAR and video fusion

In order to achieve accurate prediction and signal control of traffic flow at multiple intersections, it is first necessary to obtain high-precision and real-time traffic flow data. In this study, a traffic flow detection method based on laser radar (LiDAR) (Huang et al.,

2014) and video fusion, combined with data fusion technology, was used to obtain multi-dimensional and highly reliable traffic flow information.

LIDAR and video detection have their own advantages in traffic flow acquisition. LIDAR has high-precision distance measurement capability, can work stably under complex lighting conditions, and provides key parameters such as vehicle position and speed; while video detection can obtain the appearance characteristics of vehicles, which facilitates target identification and classification. However, LIDAR has limitations in target identification, while video detection is susceptible to weather and lighting.

In order to fully utilise the advantages of both sensors, this paper adopts a fusion method of LiDAR and video detection. Simultaneously working LiDAR and cameras are deployed at key intersections to acquire synchronised point cloud data and image sequences (Cui et al., 2020). Effective fusion of the two-sensor data is achieved through temporal synchronisation and spatial calibration.

For time synchronisation, high-precision timestamps are used to align the LiDAR and video data to ensure data consistency; for spatial calibration, the calibration plate method is used to obtain the transformation matrix between the LiDAR coordinate system and the camera coordinate system, and to establish the spatial correspondence.

The point cloud data $\mathbf{P}_t$ acquired by LIDAR contains the 3D position information of the vehicle; the video detection performs target detection and tracking on the image sequence $\mathbf{I}_t$ through a deep learning model to extract the 2D image coordinates and appearance features of the vehicle.

2.2 Application of data fusion techniques in traffic flow acquisition

After completing the temporal and spatial synchronisation, the data fusion technique is used to fuse the data from LiDAR and video detection to obtain more comprehensive and accurate information about the vehicle status $\mathbf{S}_t$.

Firstly, the point cloud data from the LiDAR is processed. A density-based clustering algorithm is used to separate the set of point clouds of each target from $\mathbf{P}_t$ to extract preliminary vehicle location information $\mathbf{L}_t$.

Next, the video images are processed. Using the trained target detection model, the vehicles in $\mathbf{I}_t$ are detected, and the image coordinates $\mathbf{C}_t$ and category information of the vehicles are obtained. Through the internal and external references of the camera, $\mathbf{C}_t$ is mapped into the LiDAR coordinate system using the projection transformation to obtain the corresponding spatial coordinates.

Then, the vehicle position $\mathbf{L}_t$ detected by LIDAR is data correlated with the mapped video detected position. For successfully matched targets, the information from the two sensors is fused to construct a comprehensive state vector of the vehicle:

$$\mathbf{s}_{i,t} = \begin{bmatrix} x_{i,t} \\ y_{i,t} \\ v_{i,t} \\ \theta_{i,t} \\ c_i \end{bmatrix}, \quad i = 1, 2, \ldots, N_t \tag{1}$$

where $x_{i,t}$ and $y_{i,t}$ denote the planar coordinate position of vehicle i at time t, $v_{i,t}$ is the velocity, $\theta_{i,t}$ is the heading angle, c_i is the vehicle category label, and N_t is the total number of detected vehicles at time t.

For unmatched targets, the respective sensor information is retained, ensuring that no vehicle data is missed. The fused data has higher accuracy and integrity.

Finally, the vehicle state data obtained from fusion is pre-processed. The data needs to be normalised in order to adapt to the input requirements of the deep learning model:

1. Missing value processing: Missing data are handled by interpolation or mean padding to ensure data integrity.
2. Outlier rejection: Statistical methods are used to detect and remove anomalous data points to avoid adverse effects on model training.
3. Normalisation: The numerical features are normalised to map the data to the [0, 1] interval, eliminating the magnitude difference and improving the stability of model training.

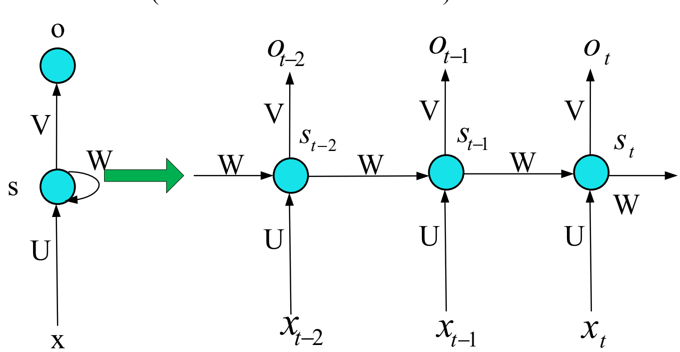
The processed traffic flow data are organised in time series to form the input tensor $\mathbf{X}_t$ of the model, which contains multi-intersection and multi-vehicle state information. By the above method, a high-quality traffic flow dataset is constructed. The fusion of LiDAR and video detection data acquisition methods, combined with data fusion technology, ensures the accuracy, real-time and comprehensiveness of the traffic flow data.

3 Improved LSTM multi-intersection traffic flow prediction model

3.1 Limitations of traditional LSTM models

The LSTM neural network structure is evolved based on the recurrent neural network (RNN) structure (Shewalkar et al., 2019), and the RNN structure is shown in Figure 1. The LSTM exhibits unique advantages in dealing with time-series data, and has been widely used in the field of traffic flow prediction due to its ability to capture both long-term and short-term dependencies in the data. However, in the task of predicting traffic flow at multiple intersections, traditional LSTM models still have obvious limitations.

Figure 1 Structure of RNN (see online version for colours)



Firstly, the traditional LSTM model usually completes training in an offline environment with fixed model parameters and lacks real-time updating capability. For dynamic and frequently changing traffic flow data, especially in multi-intersection complex traffic networks, the traffic state of each intersection has strong time-varying and uncertainty. It is difficult for the model with fixed parameters to adapt to the sudden changes in traffic flow in time, which leads to the prediction results lagging behind the actual situation and reduces the accuracy and reliability of the prediction.

Secondly, with the expansion of traffic network scale, the traditional LSTM model faces the problem of high computational complexity when dealing with multi-intersection traffic flow prediction. With the high dimensionality of multi-intersection traffic flow data, the traditional LSTM model is less efficient in processing large-scale data, and the computational cost increases significantly, making it difficult to meet the requirements of real-time prediction. This is unacceptable in real-time traffic signal control, and the excessive computational delay will lead to the signal control strategy not being able to be adjusted in time, affecting the effectiveness of traffic management.

In addition, the traditional LSTM model lacks a fast response mechanism when facing sudden changes in traffic flow. Since the model relies more on the distribution of historical data during the training process, when there are abnormal fluctuations or sudden events in traffic flow, the model cannot quickly adjust the parameters to adapt to the new data characteristics, resulting in a sharp drop in prediction accuracy. This situation often occurs in real traffic scenarios, such as congestion caused by accidents and sudden weather changes.

Combining the above factors, the traditional LSTM model in multi-intersection traffic flow prediction has limitations such as the model parameters cannot be updated in real time, the computational complexity is high, and the response to sudden changes is not timely, which limits its application effect in actual traffic signal control. In order to solve these problems, it is necessary to improve the traditional LSTM model to enhance its adaptability to dynamic changes in traffic flow and real-time processing performance, so as to more effectively serve the multi-intersection traffic signal control.

3.2 Introducing a real-time update mechanism with a sliding time window

To address the limitations of the traditional LSTM model in multi-intersection traffic flow prediction, an improved LSTM model based on sliding time window is proposed. The model achieves real-time updating of parameters by dynamically adjusting the time range of input data, while reducing the computational complexity and improving the response speed to sudden changes in traffic flow.

The improved LSTM model introduces a sliding time window W_t, where t denotes the current moment. The window size is w and contains traffic flow data from the most recent w time steps. The input tensor $\mathbf{X}_t$ of the model consists of the data within W_t and is denoted as:

$$\mathbf{X}_t = \{\mathbf{S}_{t-w+1}, \mathbf{S}_{t-w+2}, \dots, \mathbf{S}_t\} \tag{2}$$

where $\mathbf{S}_i$ is the traffic state vector at the moment i, which contains the vehicle position, speed and other information.

The sliding window mechanism enables the model to continuously receive the latest traffic flow data and update the parameters at each time step. Defining the set of parameters of the model at moment t as Θ_t, the parameter updating process can be expressed as:

$$\Theta_t = f\left(\Theta_{t-1}, \mathbf{X}_t, \mathbf{Y}_t\right) \tag{3}$$

where f is the parameter update function and $\mathbf{Y}_t$ is the actual observation. This approach ensures that the model can adapt to the dynamic changes of traffic flow and improve the prediction accuracy.

To further improve the computational efficiency, this study adopts an incremental learning strategy. An incremental update threshold δ is defined, which triggers a local update of the model parameters when the difference between the new data and the historical data exceeds δ. This approach reduces unnecessary computational overheads while maintaining the sensitivity of the model to unexpected events.

The improved LSTM cell structure contains an input gate i_t, an oblivion gate f_t, an output gate o_t and a cell state c_t. The formulae for each gate are as follows:

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{4}$$

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{5}$$

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{6}$$

$$\tilde{c}_t = \tanh\left(W_c \cdot \left[h_{t-1}, x_t\right] + b_c\right) \tag{7}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{8}$$

$$h_t = o_t \odot \tanh\left(c_t\right) \tag{9}$$

where σ is the sigmoid activation function; tanh is the hyperbolic tangent function; $\odot$ denotes elementwise multiplication; W_i, W_f, W_o, and W_c are the weight matrices; b_i, b_f, b_o, and b_c are the bias vectors.

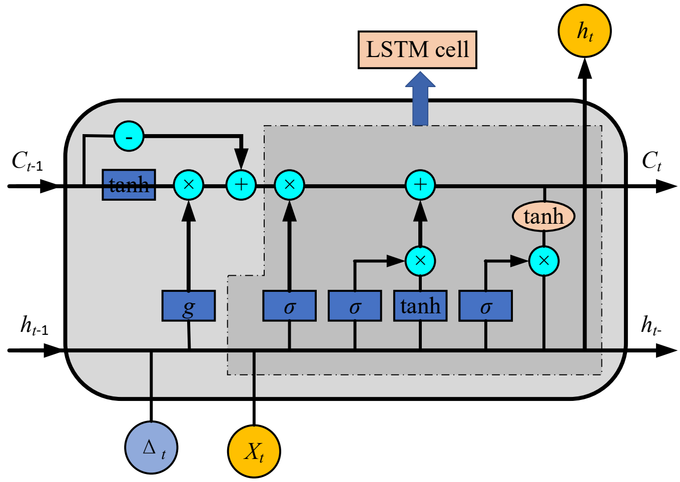
To capture the spatial correlation among multiple intersections, this model introduces the attention mechanism. Define the attention weight α_{ij}, which indicates the degree of influence of intersection i on intersection j:

$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k=1}^{N} \exp\left(e_{ik}\right)} \tag{10}$$

where e_{ij} is the correlation score between intersections i and j, and N is the total number of intersections. Through the attention mechanism, the model can adaptively adjust the importance of different intersection information to improve the accuracy of prediction.

The improved LSTM model proposed in this section achieves real-time updating of parameters through a sliding time window, an incremental learning strategy reduces computational complexity, and an attention mechanism captures spatial correlation among multiple intersections. These innovations effectively address the limitations of traditional LSTM in multi-intersection traffic flow prediction and provide a reliable prediction basis for subsequent traffic signal control. The structure of the advanced LSTM is shown in Figure 2.

Figure 2 Improved LSTM structure (see online version for colours)



4 V2X-based multi-intersection traffic signal control strategy

4.1 Application of V2X technology in traffic signal control

This section explores the innovative application of vehicle-to-circuit (V2C) V2X technology in multi-intersection traffic signal control (Garcia et al., 2021).V2X, as the core of the new generation of intelligent transport systems, provides a strong technological support to achieve accurate and real-time traffic flow prediction and control.V2X systems achieve information interaction between vehicles and infrastructure through wireless communication networks. In this study, we construct a V2X-based multi-intersection traffic information collection and processing framework. The set of intersections is defined as $I = \{i_1, i_2, \ldots, i_N\}$, where N denotes the total number of intersections. Each intersection i_k is equipped with road side unit (RSU) for communication with on-board unit (OBU) (Abboud et al., 2016).

The RSU continuously broadcasts the beacon message $B_k(t)$ containing the junction ID, location and current timestamp:

$$B_k(t) = \{ID_k, (x_k, y_k), t\} \tag{11}$$

where (x_k, y_k) are the coordinates of the intersection i_k.

The OBU receives the beacon and generates the vehicle status message $V_j(t)$:

$$V_j(t) = \{ID_j, (x_j(t), y_j(t)), v_j(t), \theta_j(t), t\} \tag{12}$$

where ID_j is the vehicle identification, $(x_j(t), y_j(t))$ is the vehicle position, $v_j(t)$ is the velocity, and $\theta_j(t)$ is the heading angle.

The RSU aggregates all vehicle state information to form the intersection traffic state matrix $M_k(t)$:

$$M_k(t) = [V_1(t), V_2(t), \ldots, V_m(t)]^T \tag{13}$$

where m is the number of vehicles within the current intersection range.

To improve the efficiency of data transmission, this study adopts an adaptive communication strategy. The vehicle state change threshold ϵ is defined, and the data upload is triggered only when the magnitude of vehicle state change exceeds ϵ:

$$\Delta V_j(t) = \left\| V_j(t) - V_j(t - \Delta t) \right\| > \epsilon \tag{14}$$

where Δt is the sampling interval and ||.|| denotes the Euclidean distance.

The V2X system also implements a vehicle trajectory prediction function. The Kalman filter algorithm is used to predict the state of the vehicle in the future $Q_k(t + \tau)$ moments based on the historical trajectory data:

$$\hat{V}_j(t + T) = F \cdot V_j(t) + w(t) \tag{15}$$

where F is the state transfer matrix and $w(t)$ is the process noise.

Based on the high-precision, real-time traffic data acquired by V2X technology, combined with the improved LSTM model proposed in Subsection 3.2, we construct a multi-intersection traffic flow prediction system. The system is able to predict the traffic flow at each intersection in the future time period in real time:

$$Q_k(t + \tau) = LSTM\left(M_k(t), M_k(t-1), \ldots, M_k(t - w + 1)\right) \tag{16}$$

where τ is the prediction duration and w is the sliding window size.

The prediction results are fed into the signal control optimisation module for dynamic adjustment of the signal timing scheme. Define the signal timing parameter vector $P_k(t)$:

$$P_k(t) = \left[\phi_1(t), \phi_2(t), \ldots, \phi_L(t), C(t)\right] \tag{17}$$

where $\phi_l(t)$ denotes the green time of the l^{th} phase, L is the number of phases, and $C(t)$ is the cycle length.

Optimising signal timing by minimising the objective function $J(t)$:

$$J(t) = sum_{(k=1)}^{N} sum_{(j=1)}^{(m_k)} \left[w_1 d_j(t) + w_2 q_j(t)\right] \tag{18}$$

where $d_j(t)$ and $q_j(t)$ denote the vehicle delay and queue length, respectively; w_1 and w_2 are the weighting coefficients; m_k is the number of lanes at intersection k.

This objective function comprehensively evaluates the operation of the whole traffic network by weighted summation of delay time and queue length at all intersections and lanes. By minimising $J(t)$, we can obtain a signal timing scheme that balances the efficiency of each intersection.

4.2 Coordinated traffic signal control methods for multi-intersections

In this section, an innovative collaborative adaptive method is proposed. The method makes full use of real-time traffic data to achieve dynamic optimisation and cooperative scheduling of signals at multiple intersections in a complex road network. The proposed coordinated multi-intersection traffic signal control method is implemented through a closed-loop adaptive optimisation process.

The V2X system collects and transmits multi-intersection traffic data in real-time, and the improved LSTM model processes and predicts these data to generate traffic flow estimates for a future period. Subsequently, a coordination mechanism constructed based on the intersection coupling degree matrix calculates the optimal phase difference to achieve green wave coordination at adjacent intersections. Meanwhile, the deep reinforcement learning algorithm dynamically adjusts the signal timing parameters of each intersection using the current traffic state, prediction results and historical performance evaluation. This process takes into account the overall efficiency of the road network and the fairness between intersections, and the control strategy is continuously optimised through the priority experience playback technique. This system continuously monitors the control effect and updates the model parameters and control strategies in real time according to the actual traffic changes, forming a closed-loop system for continuous optimisation, thus realising flexible and efficient multi-intersection cooperative control in a complex and changing traffic environment.

Firstly, we construct a multi-objective optimisation framework aiming at balancing transport efficiency and fairness. Define the road network efficiency metric $E(t)$ and the fairness metric $F(t)$:

$$E(t) = \frac{1}{N}\sum_{k=1}^{N}\frac{Q_k(t)}{C_k} \tag{19}$$

$$F(t) = 1 - \frac{\sigma\left(\{d_k(t)\}_{k=1}^{N}\right)}{\mu\left(\{d_k(t)\}_{k=1}^{N}\right)} \tag{20}$$

where $Q_k(t)$ denotes the number of vehicles passing through intersection k at moment t; C_k is the intersection capacity; $d_k(t)$ is the average vehicle delay; and σ and μ denote the standard deviation and the mean operation, respectively.

In order to achieve cooperative control of multiple intersections, we introduce an intersection coupling degree matrix G, whose element g_{ij} denotes the traffic flow association strength between intersections i and j:

$$g_{ij} = \frac{\operatorname{cov}(Q_i, Q_j)}{\sqrt{\operatorname{var}(Q_i)\cdot\operatorname{var}(Q_j)}} \tag{21}$$

where cov and var denote covariance and variance, respectively.

Based on the coupling degree matrix, we design an adaptive signal coordination mechanism. Define the phase difference $\varphi_k(t)$ of intersection k:

$$\varphi_k(t) = \sum_{j\neq k} g_{kj}\cdot\Delta t_{kj}(t) \tag{22}$$

where $\Delta t_{kj}(t)$ is the travel time between junctions k and j.

To dynamically adjust the signal timing, we propose an adaptive control algorithm based on reinforcement learning. The state space S, action space A and reward function R are defined:

$$S = \{Q_k(t), d_k(t), q_k(t) \mid k = 1, 2, \ldots, N\} \tag{23}$$

$$A = \{P_k(t) \mid k = 1, 2, \ldots, N\} \tag{24}$$

$$R(t) = w_E \cdot E(t) + w_F \cdot F(t) \tag{25}$$

where $q_k(t)$ denotes the average queue length at junction k; w_g and w_F are the weighting factors.

A deep Q-network (DQN) algorithm is used to optimise the control strategy. The Q-function approximator $Q(s, a; \theta)$ is implemented by a multilayer perceptron, where θ is a network parameter. The θ is updated by minimising the timing difference error:

$$L(\theta) = \mathbb{E}_{s,a,r,s'}\left[\left(r + \gamma \max_{a'} Q\left(s', a'; \theta^-\right) - Q(s, a; \theta)\right)^2\right] \tag{26}$$

where γ is the discount factor and θ^- is the target network parameter.

To improve convergence and stability, we use the prioritised experience replay (PER) technique. Define the sample priority p_i:

$$p_i = |\delta_i| + \epsilon \tag{27}$$

where δ_i is the timing difference error and ϵ is a small positive number.

5 Experimental results and analyses

5.1 Simulation experiment design

A series of simulation experiments are designed to fully evaluate the proposed multi-intersection traffic flow prediction and control method based on V2X and improved LSTM. The experiments aim to simulate the real urban traffic environment and verify the adaptability and effectiveness of this method under different traffic conditions.

The experimental platform adopts simulation of urban mobility (SUMO) microscopic traffic simulation software, combined with self-developed V2X communication module and traffic signal control algorithms. SUMO can accurately simulate vehicle behaviour and traffic flow dynamics, providing a reliable simulation environment for the experiment.

A typical urban road network containing $N = 9$ signal-controlled intersections constituting a 3×3 grid structure is selected for the experimental scenario. Each intersection is a standard four-way 12-lane intersection (three lanes for each inlet). The total length of the network is $L = 4.5$ kilometres, covering an area of about $A = 2.25$ square kilometres.

In order to simulate the variation of traffic demand in different time periods, three traffic patterns were designed: $\mathcal{F}_1$ (low flow), $\mathcal{F}_2$ (medium flow) and $\mathcal{F}_3$ (high flow). The vehicle generation rates for each mode are $\lambda_1 = 600$ vehicles/hour/lane, $\lambda_2 = 1{,}000$ vehicles/hour/lane and $\lambda_3 = 1{,}400$ vehicles/hour/lane, respectively. Vehicle types include small, medium and large vehicles, with the ratio set to $\rho_s{:}\rho_m{:}\rho_l = 7{:}2{:}1$.

The V2X communication parameters are set as follows: RSU communication radius $R_{RSU} = 300$ metres, OBU communication radius $R_{OBU} = 150$ metres, data transmission rate $v_{data} = 6$ Mbps, sampling period $T_s = 0.1$ seconds. To simulate the actual communication environment, data packet loss rate $p_{loss} = 0.5$ and transmission delay $\tau_{delay} \sim \mathcal{N}(20 \text{ ms}, 5^2 \text{ ms}^2)$ are introduced.

The hyperparameters of the improved LSTM model are determined by grid search: number of hidden layers n_h = 2, number of neurons per layer n_n = 64, learning rate η = 0.001, batch size B = 32, and number of training rounds E = 100. The sliding time window size is set to w = 10 minutes and the prediction duration τ = 5 minutes.

The parameters of the reinforcement learning controller are set as follows: discount factor γ = 0.95, ϵ-greedy exploration rate initial value ϵ_0 = 1.0, minimum value $\epsilon_{\min}$ = 0.01, decay rate δ_ϵ = 0.995. Memory size for priority experience playback M = 10,000, small batch size b = 64.

The experiment is divided into three phases: training phase, validation phase and testing phase. The training phase uses $\mathcal{F}_1$ and $\mathcal{F}_2$ alternating flow patterns with a duration of *Ttrain* = 48 hours; the validation phase uses $\mathcal{F}_2$ flow patterns with a duration of *Tvalid* = 12 hours; and the testing phase uses $\mathcal{F}_1, \mathcal{F}_2,$ and $\mathcal{F}_3$ flow patterns with the duration of each pattern, respectively. $\mathcal{F}_1, \mathcal{F}_2,$ and $\mathcal{F}_3$ traffic modes respectively, each lasting *Ttest* = 6 hours.

To assess the performance of the proposed method, the following evaluation metrics were selected: average vehicle delay time $\overline{d}$ (seconds/vehicle), average queue length $\overline{q}$ (metres), average number of stops $\overline{s}$ (times/vehicle), road network throughput Θ (vehicles/hour) and fuel consumption $\mathcal{E}$ (litres/100 km).

The experiments compare three methods: FTC, independent adaptive control (IAC) and coordinated adaptive control (CAC) proposed in this paper. Each method is run under the same traffic scenario to ensure the comparability and reliability of the experimental results.

Table 1 Comparison of the performance of different models in each traffic pattern

Traffic pattern	*Modelling*	*MAE (vehicles/ 5 minutes)*	*RMSE (vehicles/ 5 minutes)*	*MAPE (%)*	*Calculation time (ms)*
$\mathcal{F}_1$	LSTM	7.8	10.5	8.6	42
	Traffic-GGNN	6.2	8.4	6.9	120
	Improvement of LSTM	6.5	8.7	7.2	48
$\mathcal{F}_2$	LSTM	15.1	21.2	9.2	45
	Traffic-GGNN	11.8	16.3	7.5	128
	Improvement of LSTM	12.3	16.7	7.8	52
$\mathcal{F}_3$	LSTM	24.6	33.8	10.5	47
	Traffic-GGNN	19.2	26.1	8.4	135
	Improvement of LSTM	20.1	27.3	8.7	55

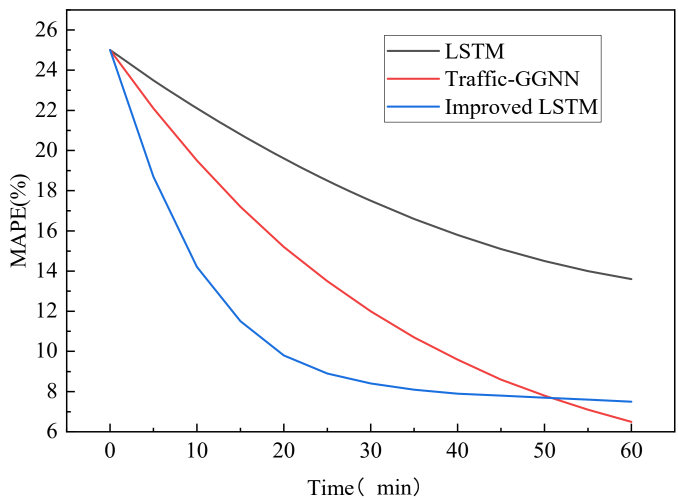
5.2 Predictive model performance evaluation

In this section, the performance of the traffic flow prediction model based on improved LSTM is evaluated and compared with the conventional LSTM model proposed by Yang et al. (2019) and the traffic-GGNN model developed by Wang et al. (2022), and the results are shown in Table 1.

The results show that the traffic-GGNN model slightly outperforms our improved LSTM model in terms of prediction accuracy in all traffic patterns, but its computational time increases significantly. In contrast, our improved LSTM model substantially reduces the computational complexity while maintaining high prediction accuracy. In particular, the performance of the improved LSTM model is closer to that of the traffic-GGNN in the high traffic ($\mathcal{F}_3$) scenario, while maintaining a lower computational time.

To further illustrate the advantages of the improved LSTM model in a dynamic traffic environment, we simulated a traffic flow mutation scenario:

Figure 3 Convergence curves of prediction errors of different models after high volume ($\mathcal{F}_3$) traffic contingencies (see online version for colours)



All models have high prediction errors at the onset of a sudden event (0 minutes). The improved LSTM model performs best in the short term (first 20 minutes), demonstrating its ability to adapt quickly. Traffic-GGNN eventually achieves the lowest stabilisation error (6.5%), which is about 1% lower than the improved LSTM (7.5%). The performance of the traditional LSTM lagged behind the other two models throughout. The improved LSTM strikes a balance between fast response and long-term stability, and although the final error is slightly higher than that of the traffic-GGNN, its ability to adapt quickly may be more valuable in real-world applications.

Table 2 MAPE of different models (%)

Traffic pattern	*Projected duration (minutes)*	*LSTM*	*Traffic-GGNN*	*Improvement of LSTM*
$\mathcal{F}_1$	5	8.6	6.9	7.2
	10	10.2	8.3	8.6
	15	12.5	10.1	10.4
$\mathcal{F}_2$	5	9.2	7.5	7.8
	10	11.5	9.1	9.4
	15	14.3	11.2	11.6
$\mathcal{F}_3$	5	10.5	8.4	8.7
	10	13.2	10.3	10.7
	15	16.8	12.9	13.4

Additional experiments were conducted to quantify the performance of the model under different prediction durations and traffic patterns (Table 2).

The results show that the performance of all models decreases as the prediction duration increases and the traffic volume increases. However, our improved LSTM model maintains a similar performance to traffic-GGNN for all prediction durations and traffic patterns, while the computational efficiency is substantially improved. In particular, the performance advantage of the improved LSTM model is more obvious in the case of high traffic ($\mathcal{F}_3$) and long prediction durations (15 minutes).

These results fully demonstrate that our proposed improved LSTM model significantly improves the computational efficiency while maintaining high prediction accuracy. In particular, it shows faster adaptability and better scalability when dealing with high and dynamically changing traffic flows. These properties make the model more suitable for practical real-time traffic control applications, especially in complex multi-intersection systems.

Through the above analysis, we verify the validity of the second innovation point of this paper: the improved LSTM model introducing the sliding time window update mechanism can guarantee the prediction performance under various traffic conditions, and at the same time, it significantly improves the computational efficiency, which is more suitable for real-time applications in practical traffic control, especially when dealing with high traffic flow and complex traffic situations.

5.3 Evaluation of signal control effectiveness

According to the experimental scheme and steps in Subsection 5.1, the performance comparison of different control methods at each flow condition is shown in Table 3.

The experimental results show that the CAC method is superior to the SAC and GNC methods in all flow conditions and evaluation indicators. The specific analyses are as follows:

1. The CAC method reduces 21.2%, 26.7% and 29.0% compared to SAC and 12.8%, 14.7% and 17.5% compared to GNC under low, medium and high traffic conditions, respectively. This indicates that the CAC method has significant advantages in dealing with complex traffic conditions, especially in high traffic conditions.
2. The CAC method achieves the shortest average queue length in all flow conditions, and the improvement over SAC and GNC increases with increasing flow rate, showing its superiority in high load situations.
3. The CAC method performs well in improving the throughput of the road network, improving 14.6% over SAC and 6.9% over GNC under high traffic conditions, effectively reducing traffic congestion.
4. The CAC method significantly reduces the number of vehicle stops, by 26.2% and 16.2% compared to SAC and GNC, respectively, under high volume conditions, improving the continuity of traffic flow.
5. The CAC method achieved the lowest fuel consumption in all flow conditions, with reductions of 13.0% and 6.9% over SAC and GNC, respectively, in high flow conditions, demonstrating its environmental contribution.

The excellent performance of the CAC method is mainly attributed to its combination of real-time traffic data provided by the V2X technology and the high-precision prediction capability of the improved LSTM model. This enables the system to respond more quickly and accurately to changes in traffic flow, especially when dealing with high traffic volumes and complex traffic conditions.

Table 3 Comparison of the performance of different control methods at various flow conditions

Flow rate	*Methodologies*	$\bar{d}$	$\bar{q}$	Θ	$\bar{s}$	$\mathcal{E}$
$\mathcal{F}_1$	SAC	38.2	25.6	3,800	1.8	7.2
	GNC	34.5	22.9	3,950	1.6	7
	CAC	30.1	19.8	4,120	1.4	6.8
$\mathcal{F}_2$	SAC	62.5	48.3	5,100	2.9	8.9
	GNC	53.7	41.2	5,450	2.5	8.4
	CAC	45.8	35.6	5,780	2.2	7.9
$\mathcal{F}_3$	SAC	95.7	76.2	5,950	4.2	10.8
	GNC	82.3	65.7	6,380	3.7	10.1
	CAC	67.9	54.3	6,820	3.1	9.4

In summary, the experimental results fully validate the significant advantages of the multi-intersection cooperative adaptive control (CAC) method based on V2X and improved LSTM in improving traffic efficiency, reducing delays and energy consumption. The method not only effectively copes with different traffic conditions, but also performs well in dealing with traffic peaks and complex road conditions, which provides strong support for the practical application of ITS.

6 Conclusions

In this paper, a multi-intersection traffic flow prediction and control method based on V2X and improved LSTM is proposed, which effectively solves the limitations of the traditional method in dealing with complex traffic environment and real-time response. By introducing V2X technology, the system is able to efficiently collect and transmit real-time traffic data, which significantly improves the accuracy and timeliness of traffic state perception. In addition, the improved LSTM model utilises a sliding time window update mechanism to further enhance the prediction capability of dynamic traffic flow, ensuring the adaptability and effectiveness of the control strategy. The following conclusions can be drawn from the simulation experiments conducted under multiple traffic flow conditions:

1 The application of V2X technology can significantly improve the real-time and accuracy of traffic data collection and lay the foundation for accurate traffic flow prediction.

2 The improved LSTM model significantly reduces the computational complexity while maintaining high prediction accuracy, making it more suitable for real-time traffic control applications.

3 The multi-intersection CAC strategy based on V2X and improved LSTM outperforms the conventional method in all performance metrics, especially in high traffic conditions.

4 The CAC strategy not only improves transport efficiency, but also demonstrates potential in reducing energy consumption and environmental protection.

The experiments in this paper were conducted mainly based on the SUMO simulation platform, which may not fully reflect the complexity of the real world, although a wide range of traffic flow conditions were simulated. Future work should consider conducting field tests in real road networks to further validate the effectiveness and reliability of this method in real traffic environments. Meanwhile, combining this method with other emerging technologies (e.g., autonomous driving, edge computing) can be explored to further enhance the overall performance of ITS.

Acknowledgements

This work is supported by the Scientific and Technological Research Program of Chongqing Municipal Education Commission (No. KJQN202101910, No. KJQN202401905, No. KJQN202301917, No. KJQN202401920)

References

Abboud, K., Omar, H.A. and Zhuang, W. (2016) 'Interworking of DSRC and cellular network technologies for V2X communications: a survey', *IEEE Transactions on Vehicular Technology*, Vol. 65, No. 12, pp.9457–9470.

Al-Khalili, A.J. (1985) 'Urban traffic control – a general approach', *IEEE Transactions on Systems, Man, and Cybernetics*, No. 2, pp.260–271.

Arnott, R. and Small, K. (1994) 'The economics of traffic congestion', *American Scientist*, Vol. 82, No. 5, pp.446–455.

Barth, M. and Boriboonsomsin, K. (2009) 'Traffic congestion and greenhouse gases', *Access Magazine*, Vol. 1, No. 35, pp.2–9.

Chow, A.H., Santacreu, A., Tsapakis, I. et al. (2014) 'Empirical assessment of urban traffic congestion', *Journal of Advanced Transportation*, Vol. 48, No. 8, pp.1000–1016.

Cui, Y., Wu, J., Xu, H. et al. (2020) 'Lane change identification and prediction with roadside LiDAR data', *Optics & Laser Technology*, Vol. 123, p.105934.

De-Palma, A. and Lindsey, R. (2011) 'Traffic congestion pricing methodologies and technologies', *Transportation Research Part C: Emerging Technologies*, Vol. 19, No. 6, pp.1377–1399.

Garcia, M.H.C., Molina-Galan, A., Boban, M. et al. (2021) 'A tutorial on 5G NR V2X communications', *IEEE Communications Surveys & Tutorials*, Vol. 23, No. 3, pp.1972–2026.

Huang, W., Song, G., Hong, H. et al. (2014) 'Deep architecture for traffic flow prediction: deep belief networks with multitask learning', *IEEE Transactions on Intelligent Transportation Systems*, Vol. 15, No. 5, pp.2191–2201.

Hunt, P. (1982) 'Split, cycle and offset optimisation technique', *Traffic Engineering & Control*, pp.190–192.

Shewalkar, A., Nyavanandi, D. and Ludwig, S.A. (2019) 'Performance evaluation of deep neural networks applied to speech recognition: RNN, LSTM and GRU', *Journal of Artificial Intelligence and Soft Computing Research*, Vol. 9, No. 4, pp.235–245.

Sims, A.G. and Dobinson, K.W. (1980) 'The Sydney coordinated adaptive traffic (SCAT) system philosophy and benefits', *IEEE Transactions on Vehicular Technology*, Vol. 29, No. 2, pp.130–137.

Viloria, F., Courage, K. and Avery, D. (2000) 'Comparison of queue-length models at signalised intersections', *Transportation Research Record*, Vol. 1710, No. 1, pp.222–230.

Wang, Y., Zheng, J., Du, Y. et al. (2022) 'Traffic-GGNN: predicting traffic flow via attentional spatial-temporal gated graph neural networks', *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 10, pp.18423–18432.

Yang, B., Sun, S., Li, J. et al. (2019) 'Traffic flow prediction using LSTM with feature enhancement', *Neurocomputing*, Vol. 332, pp.320–327.

Zhao, Z., Wang, K., Wang, Y. et al. (2024) 'Enhancing traffic signal control with composite deep intelligence', *Expert Systems with Applications*, Vol. 244, p.123020.