Topological Graph Convolutional Network-Based Urban Traffic Flow and Density Prediction

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***Abstract*— With the development of modern Intelligent Transportation System (ITS), reliable and efficient transportation information sharing becomes more and more important. Although there are promising wireless communication schemes such as Vehicle-to-Everything (V2X) communication standards, information sharing in ITS still faces challenges such as the V2X communication overload when a large number of vehicles suddenly appeared in one area. This flash crowd situation is mainly due to the uncertainty of traffic especially in the urban areas during traffic rush hours and will significantly increase the V2X communication latency. In order to solve such flash crowd issues, we propose a novel system that can accurately predict the traffic flow and density in the urban area that can be used to avoid the V2X communication flash crowd situation. By combining the existing grid-based and graph-based traffic flow prediction methods, we use a Topological Graph Convolutional Network (ToGCN) followed with a Sequence-to-sequence (Seq2Seq) framework to predict future traffic flow and density with temporal correlations. The experimentation on a real-world taxi trajectory traffic data set is performed and the evaluation results prove the effectiveness of our method.**

***Index Terms*— V2X communication, flash crowd, traffic prediction, graph convolutional network.**

I. Introduction

Cooperative Intelligent Transport Systems (C-ITS), developed based on the technology from Artificial Intelligence (AI) and big data, has attracted much attention from both academical and industrial fields in the past years [1]. Although with successful applications in C-ITS that highly improves the existing transportation systems, the novel technologies such as AI and big data [2], [3] bring novel challenges for the current C-ITS such as the reliable and efficient communication requirements for all the entities involved in the C-ITS network.

Nowadays, the existing C-ITS has deeply influenced transportation system [4]. There are already many intelligent-based transportation applications such as intelligent navigation systems, intelligent traffic flow control systems, and intelligent speed monitoring systems, etc [5]. Nowadays, the trend is to apply intelligent algorithms on both centralized C-ITS servers and the intelligent edge devices such as the on-board intelligent calculation engines on the vehicles. For instance, vehicles today always equip with cameras, communication components, and on-board computers [6] that can independently process edge intelligence algorithms for many applications [7] and share the data with the C-ITS servers. Therefore, more and more big data for the intelligent transportation system are then generated and transmitted which brings novel challenges for the communication methods for vehicles and other intelligent entities in the C-ITS. The communication between vehicles and the other intelligent entities in the transportation network can be summarized as the Vehicle-to-Everything (V2X) [8] communication which can be classified according to the communication parties [9]: Vehicle-to-Vehicle (V2V), Vehicle-to-Pedestrian (V2P), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Network (V2N). Moreover, in the near future, autonomous driving will also rely on C-ITS based communication techniques [10]. The technical foundation for implementing such C-ITS is the reliable and efficient information exchanging between the C-ITS servers and the vehicles that bring novel challenges for vehicle-related communication.

Despite various benefits brought by the development of C-ITS, some restrictions still limit the usage of V2X communication in practical. One emerging issue is latency [11], as a vital problem, which is not well provided in most current V2X communication systems especially in the urban areas. On the one hand, the V2X communication is always latency-sensitive such as the safety-related V2X information [12] that must be transmitted rapidly or the information for updating keys cannot tolerate too much latency [13]. On the other hand, since many V2X communication tasks are achieved by the proposed V2X communication standards with a broadcasting method, the reliability for such communication tasks is hard to be guaranteed.

A network architecture for V2X communications with both low latency and a high level of reliability is needed. There are many approaches to improve the communication quality for the existing V2X network [10]. However, there is a scenario existing in the urban use cases that will threaten the reliability of the V2X communication which is the flash crowd situation [14]. Different with the Distributed Denial-of-Service (DDoS) attack [15], the flash crowd in the

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urban V2X communication is not due to the malicious attackers but mainly because of the tolerance of the communication channel cannot meet the requirement of a large volume of communication between vehicles and RoadSide Unit (RSU) at specific time period such as a rush hour. Apparently, it is not reasonable to increase the communication capacity for the V2X communication system since the rush hour may only last for a short period of time. In order to solve this question, we propose a novel solution that the urban areas with the potential flash crowd situations can be predicted with the existing transportation data and can be pre-alerted.

Current research on traffic control is achieved with AI-based approaches. For instance, the intelligent traffic prediction methods [16] are used for smart navigation applications on vehicles that set routes with the traffic flow information from the C-ITS server (i.e. congestion information) after the destination is known. These methods are mainly achieved by transforming the route information into a time-related sequence of geological coordination and apply the Recurrent Neural Network (RNN) [5] to do the prediction that can be summarized as grid-based prediction methods. Later, novel methods are introduced such as the Graph Convolution Network (GCN) [17] which can better represent the traffic topology since routes are naturally graphs.

In this article, we propose a novel solution based on topological GCN solution for predicting the traffic density in urban areas that potentially suffer from the traffic flash crowd situation. The main contribution of this article can be summarized as follows. (1) We are the first to use the GCN-based solution for predicting the V2X communication flash crowd situation in the urban scenario. (2) We propose a novel topological GCN followed with the Seq2Seq model which combined the grid-based methods with the GCN-based methods. (3) We present solid experimentation with a real-world dataset to prove the effectiveness.

The roadmap for this article is as follows. In Section II, some related research background knowledge is presented. In Section III, we illustrate how to use the proposed system. In Section IV, we present the model design including the GCN and the Seq2Seq models with key details. In Section V, we explain the experiment details and evaluate the method with a real-world dataset. In Section VI, we discuss the results and give future research directions. In Section VII, we conclude our work.

II. Research Background

In this section, we list the research background mainly on two aspects. Firstly, we briefly introduce the V2X communication network. Then, the structure and the definition of the GCN are explained with some details. We also list the two main approaches of the previous work for predicting the traffic flow and density which are based on the grid-based approach and the graph-based approach respectively. We illustrate the initial research motivation of using topological GCN by illustrating the shortcomings of the current approaches for the traffic flow prediction.

A. V2X Communication Network

The V2X communication network is a heterogeneous communication network involved with different communication

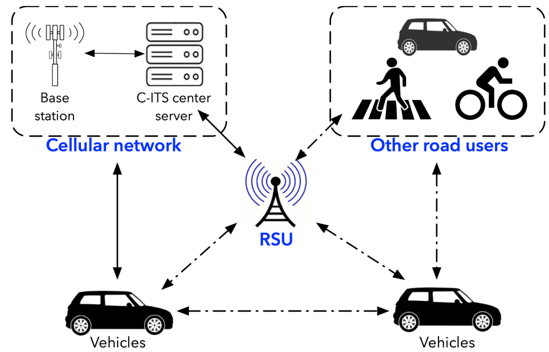

Fig. 1. Current V2X communication standards involved heterogeneous communication standards for different V2X entities.

protocols, physical communication channels, and different hardware to support communication tasks. The initial vehicle communication networks are proposed for the information sharing between the vehicles [18]. Later, with the deployment of intelligent traffic devices and the development of IoT communication technology, more and more entities in the current transportation networks become intelligent entities and got involved in the C-ITS [19].

The existing wireless communication methods cannot meet the special requirements of the novel V2X communication systems. There are many reasons such as the existing cellular-based communication standards are transmitting data through the cellular towers which are not efficient enough for the communication between vehicles and vehicles. Therefore, there are many novel V2X communication protocols proposed which can be classified into two main categories: IEEE 802.11p standard based [8] and cellular based [20]. For the IEEE 802.11p standard-based communication technology, there are Dedicated Short-Range Communications (DSRC) standards in US [21] and Intelligent Transportation System (ITS)-G5 standards in Europe [8]. In fact, IEEE 802.11p can meet most V2X application requirements with the most stringent performance specifications for the communication between the vehicles and vehicles, vehicles and RSUs, vehicles and other road users as shown in Fig. 1. However, the cellular-based communication technology such as LTE, 5G can also be used as another option to build direct and stable network links such as for communication between vehicles and remote servers [20].

In summary, the current V2X communication network is a heterogeneous communication involved with different communication standards [22]. However, due to a large number of vehicles in the urban area, the V2X communication through broadcasting with the DSRC standards may suffer from the flash crowd situation [23]. In Section III, we will introduce our proposed method to avoid the flash crowd situation for certain urban areas with the prediction of the traffic flow and density.

B. Graph Convolutional Network

Traditional convolution shows its effectiveness in extracting spatial features in regular grid data like images [24]. However, it is not applicable to a more abstract data structure like graphs. There are mainly two kinds of methods that generalize convolution to graph structure data, spectral methods, and spatial methods. The first spectral method of Graph Convolutional Network (GCN) was introduced by [25], which aims to deploy the graph convolution based on spectral graph theory. Later, this approach was extended in [26] with the implementation of fast localized convolutions to improve computation efficiency. The implementation of spectral-based GCN is also studied in image classification tasks [27]. The spatial methods directly perform graph convolutions on nodes and their neighbors, thus focus on selecting neighbors of nodes. A heuristic linear selection method was proposed by [28], which has a good performance in social network tasks.

In the field of traffic forecasting, there are also some attempts by using GCN to predict traffic, which is mainly based on spectral graph convolution. A spatial-temporal GCN is used in [29] to predict traffic speed by on graph-structured road segments data. Also based on the road segments graph, [30] applies bidirectional random walks on the graph to extract spatial dependency. In [17], a multi-graph GCN is used to forecast bike flow by fusing several bike stations graphs into an arbitrary graph. These methods outperform non-graph-based methods with the help of GCN's capability of spatial feature extraction.

C. AI-Based Traffic Prediction

The prediction work on the traffic has been investigated for a long time and has been always regarded as a key functional component in the C-ITS. Effective prediction of traffic information could improve the efficiency and performance of traffic management and control which further improves the efficiency of the transportation system.

Since the evolution of traffic flow can be considered a temporal and spatial process, as early as the 1970s, the autoregressive integrated moving average (ARIMA) model was used to predict short-term freeway traffic flow [31]. One more recent research direction is to first segment the map into grids and give coordination for these grids. With such operation, the trajectory of vehicles can be represented as a sequence of coordination values which can be predicted with neural network models such as RNN and Long Short-Term Memory (LSTM) [32]. The existing grid-based traffic prediction works proved such a method can be effectively used to predict the destination of vehicles.

However, the grid-based traffic prediction cannot represent the real situation of the traffic changing situation. For instance, the geological distance does not equal to the distance considering the time cost to arrive. In other words, two points may be close considering the geological distance but the average time cost for vehicles to arrive from one to another may be relatively long due to the traffic congestion. Secondly, among numerous grids, some of them might not contain any road or are seldom reached, which has little influence on the traffic situation of other grids. Moreover, some research works [33] that transform the whole map into a matrix for the prediction will generate sparse matrices which are unfriendly for Convolution Neural Network (CNN) [24] based approaches.

Therefore, the other research approach is trying to represent the traffic with a time cost-related distance which introduces the graph-based approach. Such approaches are mainly used

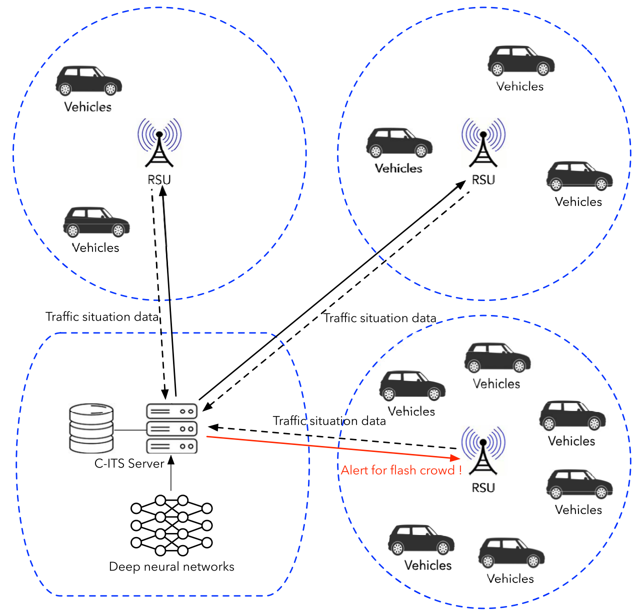

Fig. 2. System model: we propose that the C-ITS center server is able to predict the possible flash crowd areas with the traffic data collected and alert the corresponding RSUs in these areas in advance.

on the prediction for the traffic flows on highways [29] instead of urban areas. The main reason is due to the fact that a big city like Beijing or Paris contains a large number of roads which will generate huge graphs that cannot be implemented for training. Moreover, such a graph is not efficient for the traffic flow or density prediction since many of the urban areas are rarely suffered from the flash crowd situation since the maximum number of vehicles is relatively small.

III. System Designs

In this section, we present the designs of the system model that is used to predict the traffic density in the urban scenario. Firstly, as shown in Fig. 2, the traffic flash crowd situation for the V2X communication is described as when a large number of vehicles suddenly appeared in one urban area, the V2X communication capacity cannot meet the requirements of the vehicles and other communication entities. The average latency of the V2X message delivery will significantly increase since most of the V2X communication operations are done by broadcasting methods in the physical wireless communication channel.

This situation will lead to the flash crowd in V2X communication which is similar to the DDoS attack but cannot be defended since the communication requirements are not malicious. The flash crowd in V2X will lead to the failure of important or latency-sensitive information delivery such as the safety-related V2X messages [34] are missed or the key updating operations cannot be performed with the RSUs. The solution that increases the wireless communication capacity in this area is very costly since the flash crowd situation normally will not last for long.

Therefore, the prediction for the flash crowd situation in the V2X communication system is very important since, with accuracy prediction, communication task allocation can be performed to avoid the latency-sensitive information delivery such as stop the key updating in advance or to relocate

TABLE I

MAIN NOTATIONS AND DEFINITION

Notation	Definition
$\mathcal{G}$	Traffic flow graph.
A	Adjacency matrix of $\mathcal{G}$.
N	Number of nodes in $\mathcal{G}$.
$\hat{\mathcal{G}}$	Arbitrary graph extracted by GCN.
$\tilde{\mathcal{G}}$	Predicted traffic flow graph by Seq2Seq.
Θ	Ensemble of all trainable parameters in our model.

the communication protocols such as let the safety-related V2X messages have a higher priority to transmit. Such a prediction and allocation scheme may not help to reduce the vehicle number in specific areas but can effectively reduce the communication burden in these areas.

The system architecture of our research can be presented as in Fig. 2. We aim to deploy the prediction process on the C-ITS central server and to predict the flash crowd situation in the V2X topological communication network in real-time. Then, the C-ITS central server will send the alerts to the RSUs for further steps such as communication control or prioritizing the V2X messages.

IV. PREDICTION MODEL DESIGN

In this section, we give the design of how to build the Topological Graph Convolutional Network (ToGCN) based traffic flow prediction system. First, we introduce how to generate the basic graph structure of traffic data based on the novel topological graph proposal. Then, we present the prediction model which is built by using the ToGCN and the Seq2Seq structure together. The notations and their definitions are given in Table I.

A. Traffic Flow Graph Generation

As mentioned in Section II, there are some limits using grid-based structure to represent traffic flow. Instead, we consider using a graph structure. However, without geometrical information of road segments, it is inappropriate to generate a graph only with geometrical distances. Hence, we propose a novel approach to generate a traffic flow graph from vehicle GPS trajectory data. Note a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of nodes and $\mathcal{E}$ is the set of edges. For each node $v_i \in \mathcal{V}$, there is an associated value y_{v_i} representing the number of vehicles. For each edge $e_{ij} = (v_i, v_j) \in \mathcal{E}$, there is an arbitrary weight a_{ij} representing spatial relation between nodes. $A = (a_{ij}) \in \mathbb{R}^{N \times N}$ denotes the adjacency matrix containing all arbitrary weights. To generate a traffic flow graph, there are two steps: first select nodes to build the set $\mathcal{V}$, and then define arbitrary weights as well as the adjacency matrix A.

1) Node Selection: Our goal is to predict traffic flow against the flash crowd for RSUs, so areas that might probably cause flash crowds are more important. Thus, we propose a node selection mechanism to construct a graph as shown in Fig. 3. Given boundaries of latitude and longitude of a city, we first divide the city into $N_x \times N_y$ regular grids, whose size corresponds to the effective working range of RSUs. Based on this grid map, we sum the number of vehicles within each grid during the time interval to represent the traffic flow in this area. We suppose a threshold T_{crowd} according to the

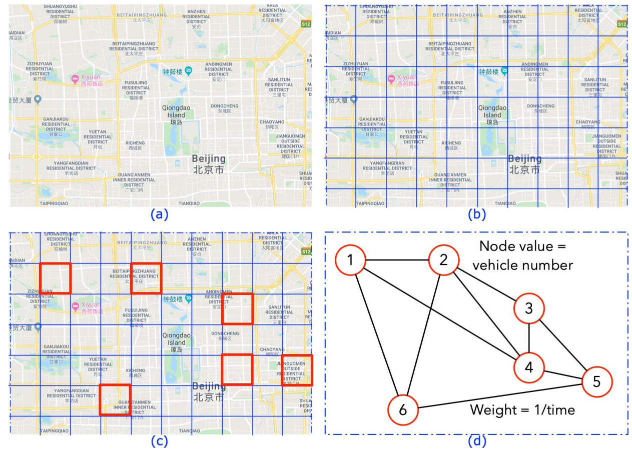

Fig. 3. Process of traffic flow graph generation. (a) Determine boundaries of original map. (b) Divide the map into regular grids. (c) Choose grids that might probably cause flash crowd as nodes. (d) Build a traffic flow graph from selected set of nodes and determine arbitrary weights between nodes.

theoretical capacity of RSUs. If the traffic flow in a grid exceeds this threshold T_{crowd} within a certain time interval, we consider that there is a flash crowd. By analyzing historical data, we select N grids that caused flash crowd for at least one time to build the set of nodes $\mathcal{V}$. The node value is assigned by the number of vehicles during the time interval. Since N is much smaller than $N_x \times N_y$, the dimensionality of data is significantly reduced, which reduces redundant information for flash crowd prediction.

2) Arbitrary Weight Definition: After nodes are selected, it is essential to determine the connectivity and interaction between nodes, which are presented by weights on edges. We propose a definition of arbitrary weights that corresponds to our task. For a pair of nodes (v_i, v_j), we first find all trajectories in historical data that pass two nodes. With these trajectories, we can calculate the average travel time between two nodes. Then we use its reciprocal as the arbitrary weight. If it takes a longer time to go from one node to the other, there is probably less interaction between two nodes. The arbitrary weight can be defined by the following formula:

$$a_{ij} = \frac{1}{\frac{1}{N_{traj}} \sum_{n=1}^{N_{traj}} T_n(v_i, v_j)} \tag{1}$$

This definition is more representative than geometrical distance because the average travel time also contains other factors like general traffic conditions between two nodes. Hence, we use this definition to represent influences on traffic flow. Experimental results show the effectiveness of this novel definition.

After node selection and arbitrary weight definition, we can get a graph $\mathcal{G}$ with an adjacency matrix A. Note that traffic flow also depends on time, we use $\mathcal{G}_t$ to represent the traffic flow graph at moment t. Finally, we get a temporal sequence of traffic flow graphs $(\mathcal{G}_1, \ldots, \mathcal{G}_n)$.

B. Model Architecture

To detect flash crowd activities with this graph-structured data, we can take advantage of different kinds of information. When looking into one graph $\mathcal{G}_t$, there are arbitrary weights on edges that represent topological relations between nodes.

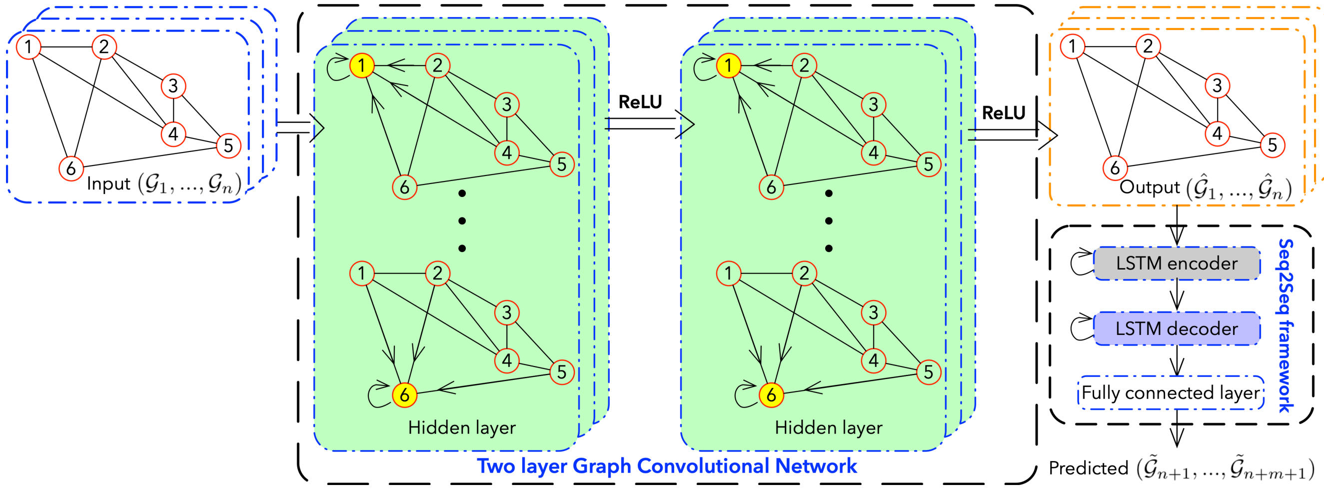

Fig. 4. The architecture of our model. The first part is two-layer GCN. The input is a temporal sequence of undirected traffic flow graphs $(\mathcal{G}_1, \dots, \mathcal{G}_n)$. For each $\mathcal{G}_t$, GCN applies graph convolution that uses graph structure and node features to get topological features of nodes. After each GCN layer, we use ReLU as activation function to introduce non-linearity. The output of GCN is a temporal sequence of arbitrary graphs $(\hat{\mathcal{G}}_1, \dots, \hat{\mathcal{G}}_n)$. The second part is a Seq2Seq prediction framework. It uses LSTM encoder-decoder architecture to consider temporal correlations of historical data and predict future traffic flow graphs $(\tilde{\mathcal{G}}_{n+1}, \dots, \tilde{\mathcal{G}}_{n+m+1})$.

When considering a sequence of graphs $(\mathcal{G}_1, \dots, \mathcal{G}_n)$, there are temporal correlations that indicate a dynamic change of traffic flow. To deal with all this information, we propose a model containing two parts, as shown in Fig. 4. In the first part, we use a multi-layer graph convolutional network (GCN). GCN takes a single graph $\mathcal{G}_t$ as input, and use graph convolution to extract topological features to get an arbitrary graph $\hat{\mathcal{G}}_t$. In the second part, we use a sequence-to-sequence prediction framework (Seq2Seq). Seq2Seq takes a sequence of arbitrary graphs $(\hat{\mathcal{G}}_1, \dots, \hat{\mathcal{G}}_n)$ as inputs, use an encoder to extract temporal correlations and use a decoder to predict the future sequence $(\tilde{\mathcal{G}}_{n+1}, \dots, \tilde{\mathcal{G}}_{n+m+1})$.

1) Topological Features Extraction by GCN: For a traffic flow graph $\mathcal{G}$, topological properties like connectivity of nodes are important for predicting traffic flow. The change of traffic flow in one node often depends on that of its neighbors. Thus, we use GCN in [35] to extract features based on topological properties. GCN can learn representation vectors for nodes from graph structure and the value of nodes. The principal is to update iteratively the representation vector of a node by aggregating representation vectors of its neighbors. For GCN, this aggregation process is defined by graph convolution. Different from traditional convolution that can only be applied to grid-based data, GCN uses graph convolution that generalizes convolution to graph-structured data. For an input graph $\mathcal{G}_t \in \mathbb{R}^{N\times D}$, where D is the length of node features, the purpose of GCN is to get an arbitrary graph $\hat{\mathcal{G}}_t \in \mathbb{R}^{N\times L}$, where L is the length of representation vector of a node. The graph convolution process can be formulated as:

$$\hat{\mathcal{G}}_t^{(l+1)} = \sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}\hat{\mathcal{G}}_t^{(l)}W^{(l)}) \tag{2}$$

where $\tilde{A} = A + I_N$, $A \in \mathbb{R}^{N\times N}$ is the adjacency matrix that we defined in Section IV-A, $I_N \in \mathbb{R}^{N\times N}$ is the identity matrix. With the identity matrix, we add self-connection to each node in order to consider its influence on itself. $\tilde{D} = \sum_j^N \tilde{A}_{ij}$ is used for normalisation, as proposed in [35]. $W^{(l)}$ is a matrix with trainable parameters for l-th graph convolutional layer, whose size can be different for each layer. σ represents the activation function, here we use ReLU. $\hat{\mathcal{G}}_t^{(l)}$ denotes the output of activation, and $\hat{\mathcal{G}}_t^{(0)} = \mathcal{G}_t$. We use two-layer GCN in our model and the detailed architecture is shown in Fig. 4. After each layer, we adapt the dropout technique during training to reduce over-fitting. The output is an arbitrary graph each node has a representation vector of size L that represents topological features. Repeating this process for each input traffic flow graph $\mathcal{G}_t$, we finally get a temporal sequence of arbitrary graphs $(\hat{\mathcal{G}}_1, \dots, \hat{\mathcal{G}}_n)$.

2) Seq2Seq Prediction Framework: GCN extracts topological relations between nodes but it is applied separately to a single graph at a time. However, temporal correlations of historical data are essential for traffic flow prediction. We consider using the Seq2Seq learning framework to further extract temporal correlations between traffic flow graphs at different times. The Seq2Seq was proposed in [36] for machine translation task. This learning framework is proved to be effective for tasks where input and output are all sequences. Furthermore, the lengths of the input sequence and output sequence are variable, which makes it flexible when adapted to different traffic scenarios. In our case, the input is a sequence of historical arbitrary graphs extrated by GCN $(\hat{\mathcal{G}}_1, \dots, \hat{\mathcal{G}}_n)$ and the output is a sequence of future traffic flow graphs $(\tilde{\mathcal{G}}_{n+1}, \dots, \tilde{\mathcal{G}}_{n+m+1})$. Seq2Seq employs a pair of multi-layer Long Short-Term Memory (LSTM) networks [37] called the encoder and the decoder. As shown in Fig. 5, the encoder, and the decoder have the same architecture, a two-layer LSTM network, but with different parameters and different functionality.

The encoder takes recursively flattened graphs in the sequence $(\hat{\mathcal{G}}_1, \dots, \hat{\mathcal{G}}_n)$ as input. At each iteration, the first LSTM layer has an intermediate output and an updated hidden state. The intermediate output is fed into the next LSTM layer. The updated hidden states are fed into the same LSTM layer but at the next iteration. Repeating this process, the encoder encodes all historical data into its final hidden states,

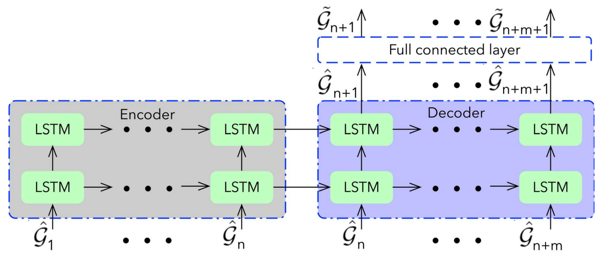

Fig. 5. Seq2Seq takes historical arbitrary graphs ($\hat{\mathcal{G}}_1, \ldots, \hat{\mathcal{G}}_n$) as input and produces traffic flow graphs ($\tilde{\mathcal{G}}_{n+1}, \ldots, \tilde{\mathcal{G}}_{n+m+1}$) as output. The encoder encodes historical data into its final states. The decoder is guided by encoder's final states and generate recursively future arbitrary graphs. There is a fully-connected layer in the decoder that convert arbitrary graphs into traffic flow graphs.

which contain information of temporal correlations. The decoder then uses encoder's final hidden states as its initial hidden states. The first input of the decoder is the arbitrary graph $\hat{\mathcal{G}}_n$. The decoder repeats the same recursive procedure as encoder to predict arbitrary graphs ($\hat{\mathcal{G}}_{n+1}, \ldots, \hat{\mathcal{G}}_{n+m+1}$) in the future. After that, we apply a fully connected layer to reduce the dimension of arbitrary graph to get traffic flow graphs ($\tilde{\mathcal{G}}_{n+1}, \ldots, \tilde{\mathcal{G}}_{n+m+1}$).

3) Model Summary: Note the entire model as a non-linear transformation $\mathcal{P}$, the prediction process can be described as:

$$\tilde{\mathcal{G}}_{n+m} = \mathcal{P}_m((\mathcal{G}_1, \ldots, \mathcal{G}_n), \Theta) \quad (3)$$

where $\mathcal{P}_m$ predicts the traffic flow graph $\tilde{\mathcal{G}}_{n+m}$ at future moment m. Θ denotes the ensemble of all trainable parameters in both GCN and Seq2Seq. Furthermore, the loss function can be formulated as:

$$L(\mathcal{P}, \Theta) = \frac{1}{M} \sum_{m=1}^{M} \|\mathcal{P}_m((\mathcal{G}_1, \ldots, \mathcal{G}_n), \Theta) - \mathcal{G}_{n+m}\|^2 \quad (4)$$

The objective is to minimize this loss function through a training procedure. The gradient related to each parameter in Θ can be obtained by using the back-propagation algorithm. Then, we apply Adam optimization [38] to tune every parameter according to its gradient with respect to the loss function and the characteristics are listed as follows.

First, the inputs of our model are graph-structured traffic flow graphs. The selection of nodes and definition of arbitrary weights correspond to our goal of traffic flow prediction against flash crowd activities.

The topological features and temporal correlations are extracted separately by two parts. Firstly, GCN converts traffic flow graphs into arbitrary weights graphs that contain topological features. Secondly, the Seq2Seq model serves as a prediction framework to predict future traffic flow graphs by using temporal sequences of graphs.

In summary, this model has several advantages when applying to traffic flash crowd prediction. The graph representation can reduce redundant information so that focus on areas that might cause a flash crowd. GCN can better extract topological relations between areas by graph convolution. By using Seq2Seq, the lengths of input and output can be dynamically changed, which makes it adaptable to different traffic flow prediction scenarios.

V. Experimentation and Evaluation

In this section, we introduce the experimentation details by illustrating the data set details and the key parameters for the implementation. Then, we list the evaluation results for the GCN model and the results for evaluating the proposed traffic prediction system are also given with both examples and statistical details.

A. Data Preparation and Implementation

In this article, we use a real-world traffic dataset in our experiments: one month Beijing taxi GPS trajectory dataset from [39]. This dataset collects trajectory data from 1st May to 29th May of around 6000-8000 taxis in Beijing city. There are in total 129 million data samples, of which 75.36% are sampled within 1 minute.

To adjust this dataset to our flow prediction task, we apply several preprocessing steps to it. We first separate the area within the fifth ring road of Beijing into 80×80 regular grids with a size of around $555m \times 425m$. We chose this size as the parameter to segment the Beijing city map into 6400 grids and this grid size could be different. According to the communication standard in current V2X [19], this size of grids will include multiple RSUs or other communication entities in the V2X network which will all be alerted for the flash crowd situation.

Based on the GPS location of taxis, we process the data samples by aggregating the vehicle numbers as the traffic density to build grid maps of traffic flow within the time interval of 10 minutes. As mentioned in section IV-A, in order to detect flash crowd activities, we choose $T_{crowd} = 1500$ as threshold and finally select 81 grids out of 6400 grids. We then use the selected 81 grids as the nodes to build a graph. The value in each node is the number of taxis. The weights between nodes are set by average travel time as in section IV-A. These traffic flow graphs are used to train and evaluate our model. The total duration of the dataset is 27 days. Traffic flow graphs of the first 22 days are used for training and the remaining 5 days are used for testing. For all tests, 60 minutes of historical data are used to predict 10 minutes of future traffic flow. We also apply data augmentation by using a moving window of 10 minutes to increase the number of samples.

We introduce some implementation details of our model. Our model is implemented by using Pytorch package [40] and on a platform with a GPU NVIDIA GeForce RTX 2080 Ti. The hyper-parameters of our model are set as follows. GCN contains two graph convolutional layers, the size of the convolution filter is 128. Both the encoder and the decoder in the Seq2Seq prediction framework have two LSTM layers with 128 hidden units.

The training process optimizes the loss function in eq. 4 by using training data. We use a mini-batch optimization with a batch size of 64. The optimisation is done by an Adam optimizer with initial learning 0.001, and $\beta_1 = 0.9, \beta_2 = 0.999$. We also apply dropout during training after each LSTM layer which is a regularisation method and helps to better generalize the model. With the dropout technique, we randomly deactivated the hidden units with a probability of 0.5. In the

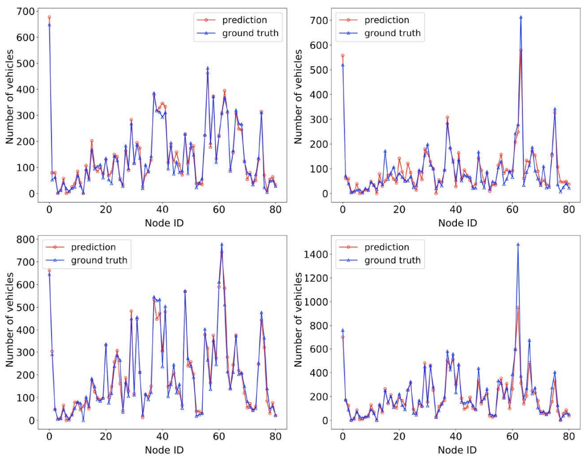

Fig. 6. Examples for comparing the predicted results with the ground truth results in four random picked time periods (total vehicle numbers appeared in the 81 nodes with a period of 10 minutes).

implementation, the model converges after about 2000 epochs, which takes about one hour.

B. Model Evaluation

In order to evaluate our model, we inference the trained model with the test data set which is the traffic flow and density for the 5 days out of the 27 days. Firstly, we show the results by some examples shown in Fig. 6. In this figure, we randomly pick four time intervals to show the comparison between the prediction results and the ground truth. In the test data set in the 5 days, we randomly pick 60 minutes to predict the next 10 minutes and compare the predicted results of traffic density with the ground truth values. The observed results showed that the difference between the prediction values with the ground truth values is very small.

Then, we evaluate the model with a statistical analysis by comparing it with the existing research works. In order to evaluate traffic flow prediction performances of different methods, we use two evaluation metrics as shown in [33].

First, we calculate the Root Mean Square Error (RMSE) which is used to measure differences between the predicted values and the ground truth values. This value is made to show the average difference between the predicted traffic density in all 81 nodes with the ground truth value and we calculate the average RMSE for all 81 nodes.

$$RMSE = \sqrt{\frac{1}{M}\sum_{m=1}^{M}\|\tilde{\mathcal{G}}_{n+m} - \mathcal{G}_{n+m}\|^2} \tag{5}$$

Also, in order to estimate the difference in a more straightforward manner, we use relative Root Mean Square Error (rRMSE) which is used to further compare RMSE with the mean of ground truth values and the results are shown in a relative manner in ratios.

$$rRMSE = \frac{\sqrt{\frac{1}{M}\sum_{m=1}^{M}\|\tilde{\mathcal{G}}_{n+m} - \mathcal{G}_{n+m}\|^2}}{\frac{1}{M}\sum_{m=1}^{M}\mathcal{G}_{n+m}} \tag{6}$$

In order to compare our method with the existing research works, we implement the baseline methods and calculate the average RMSE and rRMSE for each node as well. The baseline methods compared in this article are as follows.

- Historical average (HA): simply use the average of historical data as prediction value.
- Auto-Regressive Integrated Moving Average (ARIMA) [41]: a model that considers traffic flow change as an autoregressive integrated moving average process.
- Long Short-Term Memory (LSTM) neural network [37]: a special recurrent neural network based on gate mechanisms to deal with long-time dependency in sequence.
- Gated Recurrent Unit (GRU) neural network [42]: a variant of LSTM which has comparable performance.

TABLE II

COMPARISON OF RMSE AND rRMSE BETWEEN THE PROPOSED METHOD WITH THE EXISTING APPROACHES

	RMSE	rRMSE
HA	47.45	115.21%
ARIMA	6.347	37.84%
LSTM	3.729	8.82%
GRU	3.749	8.87%
ToGCN+Seq2Seq	**3.318**	**7.79%**

For the evaluation in this article, we calculate the average value of RMSE and rRMSE for each node and the results are listed in Table II. Our proposed method which is ToGCN+Seq2Seq has the best performance and the improvement for the RMSE and rRMSE are calculated respectively.

C. System Evaluation

We also deploy this model with the practical prediction for the flash crowd areas in our system. The evaluation metric is to calculate how many predicted areas with flash crowd situation is real. In other words, we could ignore the small prediction error in the areas with a limited number of vehicles since the alerts will not be sent to them. However, we want to achieve a high accuracy that the predicted areas with flash crowd situations are real which further makes the alerts accurate for V2X communication flash crowd.

As pointed in Section 5.2, since our Seq2Seq model was designed to predict one time interval with multiple time intervals as input sequence, we evaluated the accuracy over different input sequence size. Here we only use the best setting for system evaluation which is to use six time intervals (10 minutes each) to predict one time interval. For more prediction in the future, we iteratively use the predicted results together with the ground truth situations for predicting more future time intervals one by one.

In order to further improve the effectiveness of the proposed method, we could let the C-ITS server to alert more nodes to increase the success rate to avoid the traffic flash crowd. For instance, as shown in Table IV, the accuracy for predicting the top 10 crowded areas with our mode is 78.12%. However, if the setting is that the top 10 crowded areas are the ones needed to be alerted, we could alert the predicted top 15 crowded areas. Therefore, there will be 15 areas being alerted and the success rate to let the top 10 crowded areas to avoid the traffic flash crowd situation will be 89.04% as shown in Table III. If we set the number of alert areas as 20,

TABLE III

ACCURACY EVALUATION ON PREDICTING MORE FUTURE TIME SLOTS WITH THE TOGCN+SEQ2SEQ MODEL FOR TRAFFIC FLASH CROWD SITUATION

Prediction settings	Top 10/10	Top 15/10	Top 20/10
$\{\mathcal{G}_{n+1},...,\mathcal{G}_{n+6}\} \to \{\tilde{\mathcal{G}}_{n+7}\}$	78.51%	89.96%	93.83%
$\{\mathcal{G}_{n+1},...,\mathcal{G}_{n+6},\tilde{\mathcal{G}}_{n+7}\} \to \{\tilde{\mathcal{G}}_{n+8}\}$	67.41%	82.51%	90.37%
$\{\mathcal{G}_{n+1},...,\mathcal{G}_{n+6},\tilde{\mathcal{G}}_{n+7},\tilde{\mathcal{G}}_{n+8}\} \to \{\tilde{\mathcal{G}}_{n+9}\}$	60.83%	75.42%	85.03%
$\{\mathcal{G}_{n+1},...,\mathcal{G}_{n+6},\tilde{\mathcal{G}}_{n+7},\tilde{\mathcal{G}}_{n+8},\tilde{\mathcal{G}}_{n+9}\} \to \{\tilde{\mathcal{G}}_{n+10}\}$	54.20%	68.35%	78.92%

TABLE IV

SUCCESSFUL RATE TO PREDICT THE MOST CROWDED AREAS WITH TOGCN+SEQ2SEQ COMPARED WITH LSTM AND GRU BASED APPROACHES

	Top 5/5	Top 10/10	Top 15/15
LSTM	68.41%	73.17%	77.24%
GRU	69.10%	73.69%	77.65%
ToGCN+Seq2Seq	**75.62%**	**78.51%**	**80.34%**

the successful rate to avoid the actual top 10 crowded areas will be more than 93% as shown in Table III.

Another evaluation of the traffic density prediction is to predict more future time slots. The basic time unit used in this article is 10 minutes interval and we are trying to use the known 60 minutes to predict the next 10 minutes which can be presented as $\{\{\mathcal{G}_{n+1}, \ldots, \mathcal{G}_{n+6}\} \to \{\tilde{\mathcal{G}}_{n+7}\}$. However, with our proposed Seq2Seq structure with input data are known 6×10 minutes and output is 10 minutes, the predicted 10 minutes can be used to make further prediction with the known 5×10 minutes which is $\{\{\mathcal{G}_{n+1}, \ldots, \mathcal{G}_{n+6}, \tilde{\mathcal{G}}_{n+7}\} \to \{\tilde{\mathcal{G}}_{n+8}\}$. Although the prediction error will propagate for this further prediction, the results are still acceptable as shown in Table III. Particularly, if the prediction setting is to alert the top 15 crowded areas and we calculate the accuracy for achieving the top 10 crowded areas. As shown in Table III, the prediction for the future 30 minutes which is $\{\mathcal{G}_{n+1}, \ldots, \mathcal{G}_{n+6}, \tilde{\mathcal{G}}_{n+7}, \tilde{\mathcal{G}}_{n+8}\} \to \{\tilde{\mathcal{G}}_{n+9}\}$ will be more than 75%.

VI. DISCUSSION AND FUTURE WORK

In this article, we proposed a ToGCN+Seq2Seq model to predict the traffic density in the urban scenario to avoid the flash crowd situation in the V2X communication system. The advantage of the Seq2Seq model is flexible in the prediction settings. For instance, although the proposed model in this article was trained to predict the graph in future time slot $\tilde{\mathcal{G}}_{n+7}$ with the known sequence of graphs with a length of six: $\{\mathcal{G}_{n+1}, \ldots, \mathcal{G}_{n+6}\}$. However, the advantage of the Seq2Seq structure used in this article could allow the prediction with an arbitrary length of the input sequence of graphs. In other words, even the input sequence of graphs is shorter, the prediction can still work with an acceptable accuracy which proved the flexibility of our prediction method even with more limited traffic flow data.

We list our future work as follows. One possible direction is to further improve our model's accuracy. We will try to study more from the information get from the traffic data such as the spatial dependency of the traffic flow or the spatial-temporal distribution of the traffic flow prediction [43]. The other future research direction can be how to improve the adjacency matrix A. As mentioned in Section IV-B, the A was defined according to $\tilde{A} = A + I_N,\ A \in \mathbb{R}^{N \times N}$ in [35]. Since the A represents the weight values in the graph which is calculated based on the average time cost for the vehicles to arrive from one node to the other. In the real implementation, it is possible that one vehicle was passing from one node to the other but the route was indirect which generates a very large value of time to significantly influence the average time cost for many vehicles. Thus, in this article, we set a threshold to avoid such situations so that such extreme cases can be avoided which is novel compared with other existing approaches. According to our experimentation, our model gains performance on accuracy by setting such a threshold. However, we believe that the method to generate a better adjacency matrix or a dynamic adjacency matrix can still be investigated to further improve the prediction accuracy [44].

We would also expect some practical implementations to make our system work in real-world scenarios such as the low-level implementation for control the V2X messages or setting V2X messages with priorities to avoid communication flash crowd. Also, the other practical communication issues such as the V2X transient noise [45] could also be considered in the future work.

VII. CONCLUSION

In this article, we presented our novel traffic flow and density prediction model. This model combined the grid-based and graph-based approaches for traffic prediction which extracted the traffic flow feature with topological graph structure. Firstly, we defined an arbitrary traffic flow graph from vehicle trajectory data. Then, we used a topological graph convolutional network to extract topological features. Finally, we used a Seq2Seq framework to predict future traffic flow with temporal correlations. Based on traffic flow changes, we could further determine crowd areas so that control the communication to reduce latency. By evaluating our system with a real-world taxi trajectory dataset, high accuracy of traffic flow and density prediction was achieved.

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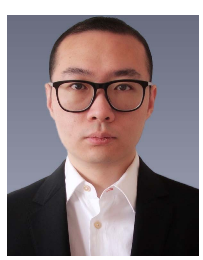

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