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Dynamic Spatial-Temporal Graph Convolutional Neural Networks Approach for Active Mode Traffic Prediction

Xiamei Wen, Panchamy Krishnakumari, and Serge Hoogendoorn

***Abstract*— Accurate short-term predictions of active mode traffic are crucial for effective urban traffic control and management, helping to reduce delays, stops, and improve travel time reliability, and optimize travel route choice. While most methods focus on motorized traffic, active modes like walking and cycling have been overlooked due to their complex dynamics and sensitivity to external factors like weather and individual choices, making them inherently less predictable. To address this, we propose a Dynamic Attention-based Spatial-Temporal Graph Convolutional Network (DyASTGCN) model that incorporates the impact of weather on graph spatial correlations within the active mode traffic network. Additionally, we introduce a fusion approach to integrate various heterogeneous spatial correlations, aiming to represent the optimal spatial correlations within the active mode network. Experimental results demonstrate that weather changes have a lagging effect on traffic network spatial correlations. Specifically, active mode traffic demonstrates significant sensitivity to precipitation, with notable changes in spatial correlations occurring within 5 minutes. Conversely, it takes approximately 20 minutes for spatial correlations to respond to wind speed influences. By incorporating both precipitation and wind speed with a 20-minute lag, our model outperforms those using only one feature, achieving the best traffic prediction performance. Given the uncertain traffic state and highly sparse nature of active mode data, our fusion approach adeptly captures the essential spatial correlations required for accurate traffic flow prediction. This allows our model to better understand complex graph correlations and traffic patterns, improving prediction accuracy and offering valuable insights into active mode network dynamics.**

***Index Terms*— Active mode, dynamic graph spatial correlations, traffic prediction, weather impacts.**

I. Introduction

RECENTLY, low-carbon transportation has gained popularity as people become more aware of the negative impacts of motorized traffic modes on the environment [1]. Active mode transportation such as walking and cycling as a sustainable, low-carbon and healthy alternative to driving is promoted in more countries [2]. However, the growing inclination towards active mode traffic introduces familiar traffic issues, such as the travel time delay, increased number of stops at (controlled) intersections, increased travel time unreliaiblity, along with new challenges, such as insufficient and narrow bike lanes and sidewalks, increasing number of accidents, etc. These factors can make users of active mode feel unsafe and encounter difficulties while cycling or walking. Furthermore, cycling or walking in bad or even extreme weather, such as high winds and thunderstorms, could increase the risk of accidents [3]. To alleviate the delays and risks faced by active mode travelers, several measures can be implemented. These include adopting traffic control and management strategies that prioritize active modes during adverse weather conditions, utilizing advanced traffic monitoring systems to optimize flow and enhance safety, and developing mobile applications that provide real-time traffic information and personalized recommendations for those using active modes. By implementing these measures, cities can create a more responsive and safer environment for pedestrians and cyclists. In this context, accurate prediction of active mode traffic is gaining significant attention from researchers owing to its crucial role in optimizing travel routes and facilitating informed decisions for transportation planning and infrastructure investment.

However, predicting active mode traffic presents unique challenges owing to its inherent uncertainty, sparse data availability, and significant noise in the datasets. Unlike traditional traffic predictions, which primarily involve motorized vehicles, prediction for active modes like walking or cycling is influenced by a multitude of factors that shape travel patterns. These factors include individual preferences dictating route choices, fluctuations in travel speeds influenced by physical conditions, and sensitivity to external elements such as weather variations, infrastructure quality, and prevailing traffic conditions. These complexities render active mode traffic more variable and less predictable compared to motorized traffic [4]. Therefore, achieving accurate predictions for active mode traffic requires a comprehensive understanding of both the temporal relationship and the uncertain spatial relationship. Existing research on active mode traffic prediction has mainly focused on predicting bike sharing usage [5]. In bike-sharing prediction, two main approaches have been utilized: traditional statistical models like regression analysis [6], and machine learning models such as neural networks [7]. These studies focus mainly on determining routes and estimating rental demand for docking stations or parking areas [8], [9], [10]. Bike-sharing systems are usually meticulously organized,

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featuring predetermined stations and docking systems. The supply and arrangement of bikes are centrally controlled, providing a high degree of system control and predictability. In contrast, private bike owners enjoy the flexibility to use their bikes according to personal schedules, destinations, and travel habits. This variability poses a challenge in collecting traffic data for private bikes and predicting bicycle traffic flow, resulting in increased uncertainty compared to the more structured and predictable nature of bike-sharing systems.

Although active mode traffic prediction might be more complex than motorized traffic, the methods developed for motorized traffic modes could still prove useful for active mode traffic prediction. In recent years, with the availability of large amounts of traffic data and the help of advanced machine learning algorithms, traffic prediction for motorized traffic modes has seen great success [11], [12], [13], [14]. Most studies focus on developing spatial-temporal traffic prediction methods to capture the change in traffic patterns over time and across different locations. For example, Yao et al. [15] proposed a Spatial-Temporal Dynamic Network (STDN) for traffic prediction, which captures the spatial and temporal information using local Convolutional Neural Network (CNN) and Long Short-term Memory (LSTM), respectively. The evaluation of the taxi data of New York City (NYC), bike sharing data from NYC, and Jinan Road camera data proved the model's effectiveness. To capture the spatial, short-term and long-term periodical dependencies of traffic patterns, Shi et al. [16] developed an Attention-based Periodic-Temporal Neural Network (APTN) model. Its prediction results outperform state-of-the-art methods. However, these methods were predominantly crafted and validated based on the traffic characteristics of motorized traffic. As a consequence, the distinctive attributes of active modes, such as sensitivity to weather conditions and the uncertainty in route selection, which can significantly influence the spatial dynamics of active modes, are not adequately captured in existing traffic models. For example, conventional graph neural networks frequently depend on fixed or adaptive adjacency matrices to extract spatial information [17]. The fixed adjacency matrix is typically constructed based on physical connections and distances between nodes, providing a static representation of network relationships. In contrast, adaptive and dynamic adjacency matrices are generated using trainable parameters, allowing them to evolve based on data-driven insights and changing conditions. However, these matrices may not fully capture the intricate details of active modes, which are highly responsive to external features and exhibit dynamic behaviors. Furthermore, the diverse types of adjacency matrices symbolize distinct spatial relationships among traffic modes. Employing a weighted averaging method [18] or a concatenation approach [17] might not be adequate to seamlessly merge this varied information into a unified adjacency matrix that captures the relationships within the graph structure. Consequently, a fused approach is necessary to integrate these heterogeneous spatial relationships effectively.

To address the challenges outlined above, this study proposes an approach called the DyASTGCN for accurate active mode traffic prediction. Furthermore, this method enhances prediction accuracy by integrating the impact of weather conditions on active mode dynamic attention data-based graph spatial correlations and effectively fusing heterogeneous spatial correlations within the active mode network.

- We investigate the impact of weather conditions on dynamic attention data-based graph spatial correlations within active mode traffic by analyzing the prediction accuracy of the proposed DyASTGCN traffic prediction model. Specifically, we examine three scenarios with different combinations of traffic flow and weather factors to derive dynamic attention data-based graph spatial correlations for active mode traffic, each scenario incorporating various lag sizes between traffic flow and weather conditions. Experimental results reveal that weather significantly impacts active mode traffic, with weather effects exhibiting a lagged influence on changes in spatial correlations.
- To capture the optimal representation of graph spatial correlations in active mode traffic, we proposed a heterogeneous spatial correlation fusion approach. This method aggregates multiple heterogeneous spatial graph correlations including predefined distance-based graph correlations, parameter-based adaptive graph correlations, and dynamic attention data-based graph correlations within the active mode network to enhance traffic prediction accuracy. Experimental results reveal that the fused graph spatial correlations provide the best representation of the spatial dynamics of active mode traffic, when compared to other individual graph correlations. Consequently, the prediction results of the DyASTGCN model, which utilizes the fused graph spatial correlations, outperform those based on other individual graph correlation methods.
- Given the temporal and spatial characteristics of active mode traffic, we introduce the DyASTGCN model to predict traffic flow accurately. This model leverages multi-head self-attention to capture intricate temporal relationships and utilizes Graph Convolution Networks (GCN) to incorporate spatial information, including weather influences and heterogeneous spatial correlations within the active mode network. Our prediction results demonstrate that DyASTGCN outperforms baseline models in forecasting active mode traffic.

The rest of this paper is structured as follows. Section II provides an overview of related work in the field of active mode prediction. Section III details the methodology of our proposed model. Section IV covers our data, including data collection and filling approaches, the dataset used for assessment, experimental configurations, as well as the findings and analysis from our experiments. Section V discusses the implications and contributions of our work.

II. Related Work

In this section, we first review the existing traffic prediction studies. We then explore research on traffic prediction using graph neural networks, particularly focusing on how these studies capture the spatial correlations of the graph network for prediction. Finally, we review studies that address heterogeneity in traffic networks.

A. Traffic Prediction

Predicting traffic is a vital element of the intelligent transportation system [19], [20], [21] and plays a key role in contemporary traffic control and management. With the growing volume and variety of available traffic data, data-driven methods, including statistical methods, traditional machine learning methods, and deep learning methods, have gained significant attention in traffic prediction research [22]. Especially deep learning methods that can be highly effective for predicting traffic patterns in real time and can adapt to changes in traffic flow patterns over time [23], [24], [25]. Duan et al. [26] proposed a deep hybrid neural network by integrating a Convolutional Neural Network (CNN) and Long Short-term Memory (LSTM) to predict urban traffic flow using real GPS taxi trajectory data from Xi'an city. A greedy policy is used in training to reduce computation time; experimental results show that the proposed method outperforms existing methods. Similarly, Wu et al. [27] integrated deep Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) as a novel traffic flow prediction method that can capture the spatial and temporal features to predict traffic flow; the experimental results show that the proposed method can learn specific knowledge from large traffic flow data. However, these traffic prediction methods are developed primarily for motorized traffic modes.

For active mode traffic prediction, because of its complexity, lack of data and sensitivity to external factors (e.g., weather), it is more difficult to capture traffic patterns accurately on the road network. Existing studies on active mode mainly focus on bike-sharing systems [28], [29], [30]. For example, to predict the number of bicycles rented and returned to each parking station, Li et al. [31] developed a hierarchical prediction model and evaluated its performance in two bike-sharing systems in New York City and Washington, DC, respectively, which shows the advantage of the model. However, these studies primarily focus on predicting demand at fixed stations for bikes, thereby ignoring the traffic state of shared bikes on the road network. Additionally, predicting traffic patterns for active modes such as private or shared bicycles on road network, which lack fixed stations or parking zones, remains more unpredictable due to the uncertainty surrounding trip origins and destinations.

B. Graph Neural Networks on Traffic Prediction

The advent of Graph Neural Networks (GNNs) has significantly enhanced the capacity to investigate spatial relationships in traffic prediction. GNNs are specifically engineered to capture non-Euclidean spatial structural data, which aligns more closely with the intricacies of the structure of the traffic network [32]. In this context, capturing the complexity and nonlinear traffic patterns seems possible when combining GNNs with existing temporal dependencies learning models [33]. For example, Zhao et al. [34] proposed a novel network-based Temporal Graph Convolutional Network model (T-GCN), which could simultaneously capture spatial and temporal dependences to predict road traffic based on the SZ-taxi dataset and the Los-loop dataset. To achieve an accurate prediction of traffic flow, Li et al. [35] explored the spatial-temporal features in traffic flow using a Graph and Attention-based Long Short-Term Memory Network (GLA); The results show that this method performs better than most previous methods based on PeMS dataset. However, these studies mainly predefined the graph structure relationship based on the Euclidean distance or learned the graph structure relationship according to some attributes of the road network, such as POI distribution and regional function, which is insufficient to contain all the valuable information for the complicated active mode traffic prediction scenario.

Some graph-based traffic prediction approaches aim to learn the underlying dependencies of graph relationships adaptively. Wu et al. [36] proposed Graph WaveNet for spatial-temporal graph modeling, which retains the dependency matrix by capturing hidden spatial dependencies in the data in an adaptive way. Zhang et al. [18] designed four different types of relationships between nodes—origin-destination (OD) relationship, transfer relationship, distance relationship, and correlation coefficient relationship to help adaptively exploit hidden correlations between nodes. These studies could capture the underlying spatial relationships between nodes adaptively to some extent. However, the spatial relationships might vary over time depending on traffic conditions and the traffic network environment. To address the dynamic nature of spatial relationships, Hu et al. [37] designed a graph learning module to learn spatial dependencies in the traffic network based on input data, complemented by a dilated causal convolution network with a gating mechanism to capture long-term temporal correlations in the traffic data. Additionally, Ta et al. [17] developed an Adaptive Spatial-Temporal Graph Neural Network (ASTGNN) for multi-step traffic condition forecasting, which captured the optimal graph structure considering node attributes and complex spatial-temporal correlations using a spatial-temporal convolution architecture. However, active modes traffic are influenced by weather conditions and the physical well-being of travelers, introducing a higher level of complexity in their spatial relationships compared to traditional traffic modes. Given this context, there is an increasing demand for novel traffic prediction methods capable of capturing these uncertain spatial relationships inherent in active modes.

C. Heterogeneous Spatial Correlations Handling in Traffic Networks

Existing graph architectures are often developed for homogeneous graphs with identical types of nodes and edges. For example, some researchers have focused on graph embedding for undirected and unweighted homogeneous graphs, considering only the structural information of the graph [38]. To extract more information from the graph, weighted graphs with identical types of nodes and edges have also been explored [39]. Some studies have considered directed graphs, which can provide a more precise graph representation [40].

However, these approaches are not well-suited for graphs that contain different types of nodes and edges, as they cannot properly capture the intricate representation and interaction of diverse types of nodes and edges within a graph. To address this limitation, researchers have developed methods for heterogeneous networks. For example, Chang et al. [41] designed a deep embedding algorithm to capture correlations between heterogeneous data in a network, demonstrating the effectiveness and scalability of their approach. In traffic systems, the represented graphs of traffic networks also contain various types of nodes and edges, including weighted edges based on distance, similarity functions, and traffic patterns, as well as nodes from different traffic modes. Several studies have explored traffic patterns and characteristics in heterogeneous traffic networks. For instance, Liang et al. [42] proposed a Multi-Relational Spatial-Temporal Graph Neural Network (ST-MRGNN) for multimodal demand prediction, accounting for diverse spatial units and heterogeneous spatial-temporal correlations across subway and ride-hailing modes. This model outperforms existing methods. Similarly, Guo et al. [43] developed an Attention-based Spatial-Temporal Graph Neural Network (ASTGNN) for highway traffic prediction by considering periodicity and spatial heterogeneity through embedding modules, surpassing state-of-the-art baselines. Given this context, exploring heterogeneous dynamic graph relationships in active mode is crucial for accurately capturing and understanding traffic patterns.

III. Proposed Methodology for Active Mode Traffic Prediction

In this section, we begin with a brief overview of the definition and problem statement of this study. We then delve into the methodology employed to capture the various spatial correlations within the active mode network traffic and the approach used to fuse these spatial correlations to achieve optimal spatial correlations for active mode traffic. Finally, we systematically present the structure of the proposed DyASTGCN model for active mode traffic prediction.

A. Definition and Problem Statement

Definition (Graph traffic network): To streamline computations while effectively capturing significant traffic patterns, we define the traffic network as an undirected graph $\mathcal{G} = (\mathcal{G}_1, \mathcal{G}_2, \ldots, \mathcal{G}_t)$, where $\mathcal{G}_t = (V, E, \mathbf{A}_t)$ denotes the active mode graph at time t, V is the set of nodes representing sensors that record the traffic flow of active modes on the road network; E is a set of edges; and $\mathbf{A}_t \in \mathbb{R}^{\mathbb{N}\times\mathbb{N}}$ is the adjacency matrix of $\mathcal{G}_t$ with N nodes at time t recorded as a weighted adjacency matrix.

Problem (Multi-step active mode traffic prediction): The historical active mode traffic data for each input includes data from the past hour, represented as: $\mathbf{X} = (\mathbf{X}_{t-k+1}, \mathbf{X}_{t-k+2}, \ldots, \mathbf{X}_t) \in \mathbb{R}^{N\times F\times T_k}$, where T_k are the time steps of each input, $\mathbf{X}_t = (\mathbf{x}_{t,1}, \mathbf{x}_{t,2}, \ldots, \mathbf{x}_{t,N}) \in \mathbb{R}^{N\times F}$ indicates the vector of characteristics of each node v at time t, F is the dimension of the characteristic of each node. Our goal is to find a function f to predict the following T time steps data $\hat{\mathbf{x}} = (\hat{\mathbf{x}}_{t+1}, \hat{\mathbf{x}}_{t+2}, \ldots, \hat{\mathbf{x}}_{t+T}) \in \mathbb{R}^{N\times F\times T}$, that is:

$$(\hat{\mathbf{x}}_{t+1}, \hat{\mathbf{x}}_{t+2}, \ldots, \hat{\mathbf{x}}_{t+T}) = f_\theta((\mathbf{X}_{t-k+1}, \ldots, \mathbf{X}_t), \mathbf{A}_t) \tag{1}$$

here, θ represents the learnable parameters of the function. Considering the sensitivity of active mode traffic to external factors, our approach utilizes the most recent hour of historical data as input to predict the traffic for the subsequent hour.

B. Graph Spatial Dependencies Learning

Active mode traffic graph spatial correlations encompass various types of relationships. Within a traffic network, the flow at a road section is influenced by its connections, suggesting that distance-based predefined graph correlations can reflect the geographic network correlations for active modes. Additionally, different road structures and facilities can impact these correlations, which could be explored through a parameter-based adaptive graph [36]. Furthermore, surrounding traffic patterns and weather conditions contribute to changing spatial correlations over time in the active mode network. To capture these dynamics, we introduce a dynamic attention data-based graph correlation matrix to model active mode spatial correlations.

However, these individual spatial correlations only capture partial aspects of the spatial relationships in active mode traffic. To comprehensively capture the overall graph correlations in active mode, we introduce a fusion approach. This method integrates these heterogeneous graph correlations to derive optimal spatial relationships for the analysis of active mode traffic.

1) Distance-Based Predefined Graph Spatial Correlations Learning: Spatial proximity between sensors often implies similarity in the traffic patterns they detect. Therefore, we model the sensors as nodes in a graph, where the connectivity between two nodes is determined by the shortest path obtained using Dijkstra's algorithm [44] based on the active mode road network. To capture the spatial dependency, we define the edge weights based on the distance of the shortest path between two nodes, employing a threshold Gaussian kernel weighting function [45] as follows,

$$A_d^{i,j} = \begin{cases} \exp(-\dfrac{|\mathrm{dist}(i,j)|^2}{2\theta^2}) & \text{if } dist(i,j) < K \\ 0 & \text{else} \end{cases} \tag{2}$$

where $A_d^{i,j}$ denotes the distance weight of the graph, with $|\mathrm{dist}(i,j)|$ representing the shortest path distance between node i and node j. Here, θ signifies the standard deviation of distances, and K serves as the threshold.

2) Parameter-Based Adaptive Graph Spatial Correlations Learning: Active mode traffic flow is highly dynamic, influenced by various factors such as events, accidents, traffic lights, road connectivity, and surrounding environmental conditions. These factors introduce complexities in capturing active mode spatial correlations. Parameter-based adaptive methods offer flexibility in adjusting the correlations between nodes. Therefore, a parameter-based adaptive graph structure learning method [36] is utilized to capture the hidden spatial

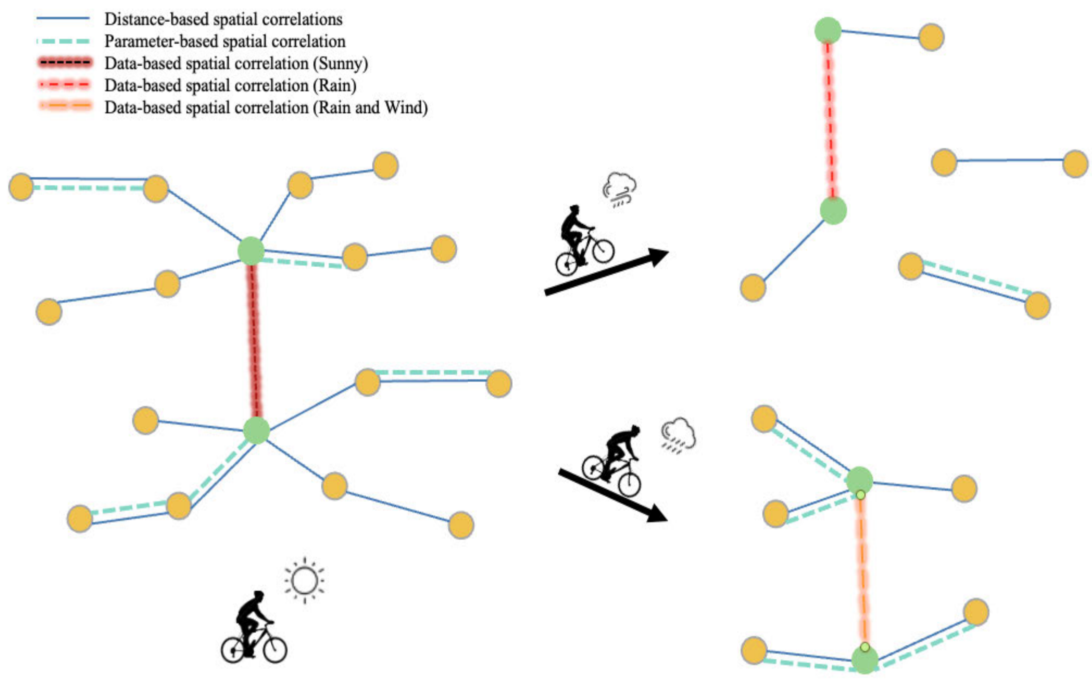


Fig. 1. Framework of the overall model.

dependencies within the active mode graph. This method utilizes two embedding dictionaries with learnable parameters to derive the spatial dependency weight among nodes $\mathbf{E}_1$,$\mathbf{E}_2 \in \mathbb{R}^{\mathbb{N}\times\mathbb{P}}$, as follows,

$$\mathbf{A}_a = SoftMax(ReLU(\mathbf{E}_1\mathbf{E}_2^T) \tag{3}$$

where P is the hidden dimensions of each node. $\mathbf{E}_1$ is the source node embedding dictionary, $\mathbf{E}_2$ is the target node embedding dictionary. ReLU is an activation function used to introduce nonlinearity into the matrix and ensure the values in matrix $\mathbf{A}_a$ are non-negative. The SoftMax function is then applied to normalize the matrix, converting it into a probability distribution where the sum of the values is equal to 1.

3) Dynamic Attention Data-Based Graph Spatial Correlations Learning: Geographical proximity alone may not adequately capture spatial correlations between nodes, as unconnected nodes can exhibit stronger correlations than those in close physical proximity. For instance, nodes with similar functions or roads at the same hierarchy level may demonstrate similar traffic patterns, even if they are geographically distant. Therefore, capturing spatial correlations based on traffic flow feature involves exploring pattern similarities that do not rely on geographical closeness. Moreover, active mode traffic is notably susceptible to various external factors, particularly bad weather conditions. These factors can significantly impact cyclists' route choices or prompt shifts to other traffic modes, thereby increasing the uncertainty, complexity, and difficulty of capturing the spatial correlations within the active mode traffic network based on traffic flow feature. Weather changes do not immediately impact traffic spatial correlations; their effects manifest gradually. For example, consider a sudden onset of rain during peak commuting hours. Initially, there might be a minor reduction in the number of cyclists on the roads, as some individuals might continue their commute despite the rain. However, as the rain persists and intensifies, more cyclists may opt to seek shelter or switch to public transportation. This gradual shift in behavior alters the spatial correlations within the traffic network over time, as illustrated in **Fig. 1**. This lag in the manifestation of weather effects highlights the importance of capturing dynamic, evolving spatial correlations for accurate traffic predictions.

To investigate the spatial correlations of active mode traffic based on traffic flow features and how variations in weather information alter these correlations, we first propose employing an attention mechanism, as shown in Equation 4, to capture the dependencies of traffic flow features and weather information for each sensor.

$$\mathbf{M}_{at,i} = attention(\mathbf{M}_{tq,i}, \mathbf{M}_{tk,i}, \mathbf{M}_{tv,i}) \tag{4}$$

where $\mathbf{M}_{t,i}$ is the traffic flow input sequence and the corresponding weather data for prediction at time t, $\mathbf{M}_{t,i}$ is projected onto separate learned linear subspaces to obtain the queries, keys, and values $\mathbf{M}_{tq,i}$, $\mathbf{M}_{tk,i}$, and $\mathbf{M}_{tv,i}$ of attention mechanism, respectively. $\mathbf{M}_{at,i}$ represents information dependencies of the traffic flow feature and weather information that are most relevant for capturing spatial correlations. In this paper, $attention(\cdot)$ function is a Scaled Dot-Product Attention [46] as follow,

$$attention(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = softmax(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_m}})\mathbf{V} \tag{5}$$

where $\mathbf{Q}$, $\mathbf{K}$ and $\mathbf{V}$ are the query, key and value, respectively; d_m is the scaling factor, which is used to balance the complexity and capacity of the model.

After obtaining the dependency representations of each sensor, we derive the spatial pattern similarity between the sensors by calculating the dot product [17] of the dependency

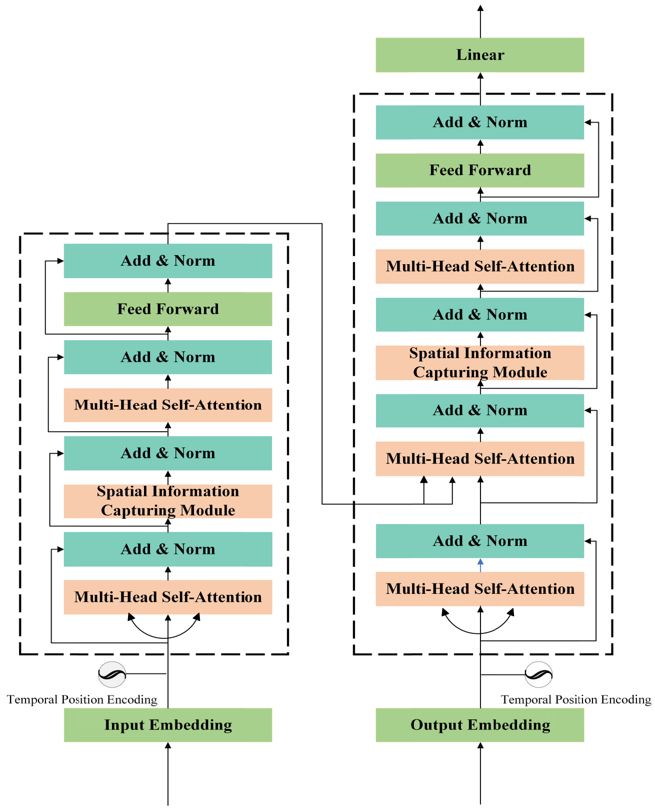


Fig. 2. Active mode traffic prediction module.

representations between sensors, as follows:

$$\mathbf{A}_{t,attri} = ReLU(\mathbf{M}_{at}\mathbf{M}_{at}^{T}) \tag{6}$$

where $\mathbf{M}_{at}$ is the matrix of the representations of all sensors with utmost pertinent details of traffic data for the spatial correlations extraction at time t; $\mathbf{M}_{at}^{T}$ is the transpose of $\mathbf{M}_{at}$; $\mathbf{A}_{t,attri}$ is the dynamic attention data-based adjacency matrix at time t.

4) Heterogeneous Graph Spatial Correlations Fusion Approach: The representation of spatial correlations in a graph can be complex and multifaceted. Not only does a physical relationship, such as a distance-based predefined graph, play a role in describing the graph, but also a semantic or contextual relationship, such as a self-adaptive graph or a dynamic attention data-based graph, is essential in capturing the graph's relationships between nodes. These diverse types of graph representations can provide complementary information to the relationships between nodes. However, balancing the utilization of these graphs with different types of edge directly in a graph architecture can be challenging. To address this challenge, we have designed a fusion approach to derive an optimal graph for active mode spatial correlations representations.

Specifically, we first concatenate all matrices along the feature dimension as shown in equation 7.

$$\mathbf{A}_{t,all} = concat(\mathbf{A}_{d}, \mathbf{A}_{a}, \mathbf{A}_{t,attri}) \tag{7}$$

To get a fully represented graph structure based on the heterogeneous graph spatial relationship, we apply two-layer 1D convolutions to capture optimal graph correlations of active mode.

C. Short-Term Active Mode Traffic Prediction

Active mode traffic is flexible and subject to change based on personal choices, motives and trip purposes, and preferences. To make an accurate traffic prediction for active mode, we develop a spatial-temporal traffic prediction module based on the Transformer encoder-decoder structure as shown in **Fig. 2**, which allows for the capture of complex relationships of spatial and temporal characteristics, enabling the model to effectively learn and predict dynamic changes in active mode traffic. Specifically, we adopt a "sandwich structure" [47] in both the encoder and decoder. This structure comprises two multi-head self-attention layers to capture temporal information of the traffic flow, with a spatial information capturing module in between to capture spatial information. To facilitate deep training, we integrate residual connections and layer normalization between each layer. The comprehensive design incorporates one encoder layers and one decoder layers, providing the model with the capability to proficiently acquire and anticipate spatial-temporal traffic patterns.

1) Temporal Dependency Learning: Given the unpredictable nature of traffic patterns in active modes, extracting crucial dependencies from historical traffic flow data becomes essential to improve prediction accuracy. However, handling long sequences of data can potentially lead to the loss of vital information during the learning process. To address this challenge, we propose integrating the multi-head self-attention module into our model. This module, derived from the Transformer architecture [46], allows the model to selectively focus on different segments of the input sequence. This capability ensures that temporal dependencies are effectively captured, enabling the model to retain and utilize significant information for more accurate traffic predictions.

The multi-head self-attention module, while highly effective in capturing global dependencies between input elements, is not explicitly designed to model the order of the input sequence in the same way as recurrent or convolutional neural networks. In applications such as active mode traffic prediction, the temporal order of the input sequence plays a critical role in capturing important information for accurate prediction. For instance, weather and traffic conditions at a particular time are likely to be more similar to those at subsequent time steps. To account for this, it is necessary to place more weight on information that is closer to the prediction time, especially when dealing with active mode traffic with uncertain patterns. By emphasizing the importance of recent data, models can more effectively capture the temporal dependencies between input elements and improve their predictive performance. Therefore, we combine the fixed positional encodings [46] with the input embeddings so that multi-head self-attention module could still make use of temporal order information of traffic data. The equations are shown below,

$$P_{(pt,2dim)} = \sin(pt/10000^{2dim/d_m}) \tag{8}$$

$$P_{(pt,2dim+1)} = \cos(pt/10000^{2dim/d_m}) \tag{9}$$

where pt is the position index of the traffic flow input sequence; dim is dim-th dimension of the positional encoding vector; d_m is the dimension of the positional encoding, which is the same as the dimension of input embeddings, so that they could be added element-wise.

2) Spatial Dependency Learning: To explore the geographic and hidden spatial correlations of the active mode graph network, the spatial Graph Convolutional Network (GCN) [48] can be used. The spatial-based GCN is a type of neural network that can operate on non-Euclidean graph-structured data, allowing it to learn feature representations by aggregating the features of a node's neighbors and incorporating both local and global information in the graph.

In the context of active mode traffic flow prediction, the graph represents the spatial correlations between different sensors, and each node represents a specific sensor. The spatial-based GCN operates by conducting successive graph convolutions on the input traffic flow features using a dynamic adjacency matrix $\mathbf{A}_{t,f}$. This matrix updates the feature representations of each node by incorporating the traffic flow features of its neighbors. In our model, the input adjacency matrix comprises the output of a heterogeneous graph spatial correlations fusion approach. This approach considers the spatial correlations influenced by weather and integrates heterogeneous features from various types of spatial correlations. The output of the Spatial-based GCN is a set of new traffic flow feature representations for each node. Specifically, this spatial-based GCN is able to handle large graphs by expanding the adjacency matrix to incorporate additional connections, without fundamentally changing the architecture.

$$GCN(\mathbf{X}_t) = ReLU(\hat{\mathbf{D}}^{-1}\hat{\mathbf{A}}_t\mathbf{X}_t\mathbf{W}) \tag{10}$$

where $\hat{\mathbf{A}}_t = \mathbf{A}_{t,f}$; $\hat{\mathbf{D}}_{ii} = \sum_j \hat{\mathbf{A}}_{ij}$, $\mathbf{W}$ is the trainable weight matrix. $ReLU(\cdot)$ is an activation function.

3) Residual Connection and Feedforward Networks: To mitigate the vanishing gradient problem and enhance model performance, we incorporate residual connections between each layer, as shown in the equation 11. Additionally, a fully connected feedforward network [46] is introduced to each encoder and decoder layer, enabling the model to learn complex input-output relationships and introducing nonlinearity as depicted in the equation 12.

$$\mathbf{X}^{l+1} = layer(\mathbf{X}^l) + \mathbf{X}^l \tag{11}$$

$$FeedForward(\mathbf{X}) = ReLU(\mathbf{X}\mathbf{W}_0 + b_0)\mathbf{W}_1 + b_1 \tag{12}$$

where $layer(\mathbf{X}^l)$ is the output of layer l, $\mathbf{X}^l$ is the input of layer l, $\mathbf{X}^{l+1}$ is the output after residual connection. $layer(\cdot)$ is the temporal or spatial information capturing operation function.

4) Multi-Step Traffic Prediction: In the reference section of this model, we will employ an autoregressive inference to forecast traffic conditions over multiple future time steps. This involves using the previously generated prediction result as the input to predict the next time step. This approach provides a more comprehensive and extensive view of anticipated traffic conditions, offering valuable insights for various applications in transportation planning, management, and decision making.

IV. Experimental Results and Benchmarking

In this section, we present the result of applying the proposed approach. Before presenting the results, we will first provide an overview of the experimental set-up, including a description of the data, the metrics used for performance assessment, and the baseline models used in this paper.

A. Dataset Description

To evaluate the effectiveness of our proposed model, we conducted experiments using real-world bicycle traffic flow data from the National Road Traffic Data Portal of the Netherlands. This dataset, collected by loop detector sensors in Rotterdam, spans from January 1, 2022, to December 31, 2022, and includes data from 21 sensors. As shown in **Fig. 3**, the sensors are sparsely distributed. Missing data were imputed using the average data from the corresponding time spots over the previous two days. The dataset was aggregated into 5-minute intervals, resulting in 12 data points per hour. Standard normalization was applied to the input dataset to enhance model convergence and stability during training. Our objective was to perform multi-step active mode traffic predictions, using one-hour historical data (12 data points) to predict traffic for the next 60, 45, and 15 minutes. To maintain evaluation integrity, the dataset was divided chronologically into training, validation, and test sets with a split ratio of 6:2:2.

The weather feature data from the Royal Netherlands Meteorological Institute (KNMI) at the Rotterdam Station was utilized. This dataset includes hourly observations of precipitation amounts and mean wind speeds. Precipitation data reflects

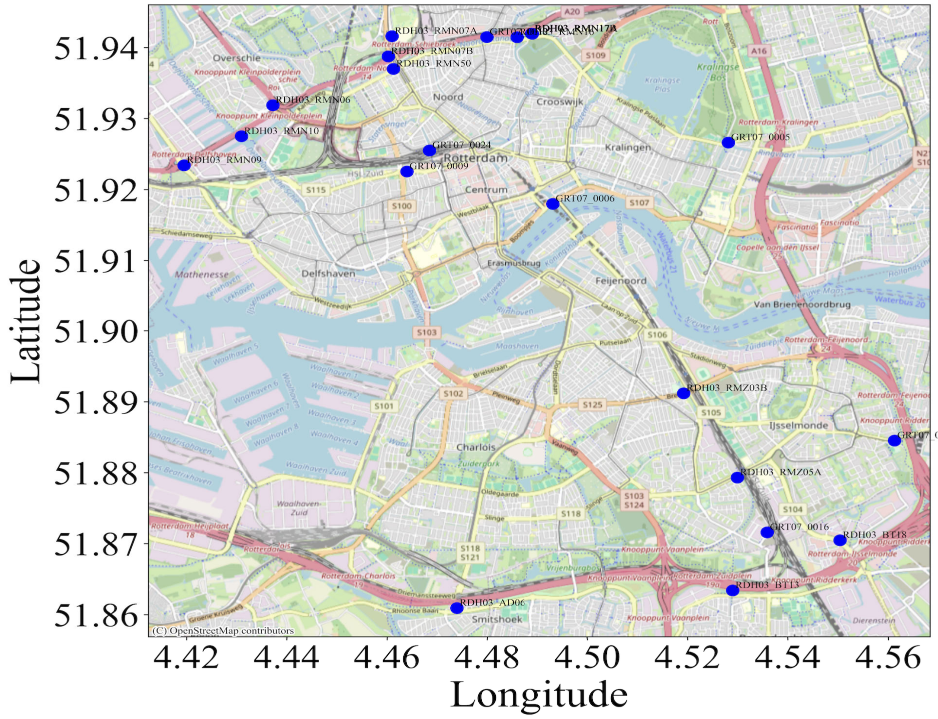
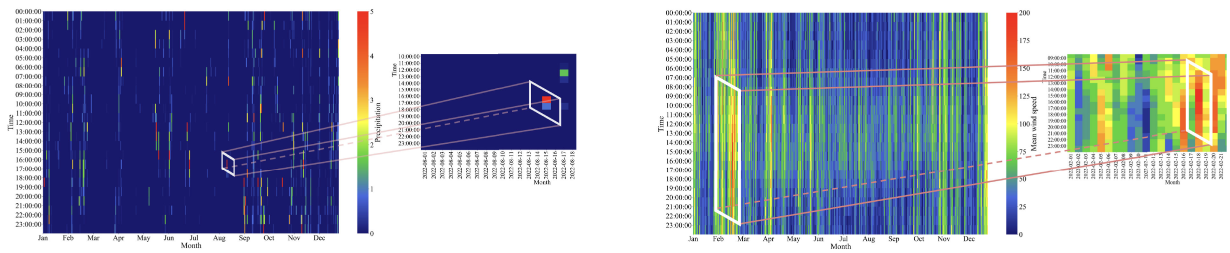


Fig. 3. Location of sensors in Rotterdam (2022).



(a) (b)

Fig. 4. Overview of weather in Rotterdam (2022). (a) Precipitation. (b) Mean wind speed.

the millimeters of rain recorded during the preceding hour. The mean wind speed (in 0.1 m/s) is recorded for the hour preceding the observation timestamp. Since the weather data is provided at hourly intervals, each data point was divided into 12 intervals. Specifically, the mean wind speed data was duplicated for each interval, while the precipitation data was evenly distributed across the intervals to represent the average millimeters of rain over 5 minutes. The timestamps of these weather data intervals were then aligned with or lagged by 5 to 30 minutes from the traffic flow data timestamps to be incorporated into the model.

B. Evaluation Metrics

In this paper, the prediction results of active mode traffic flow are evaluated by Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Weighted Absolute Percentage Error (WAPE). The formulations to calculate these metrics are shown below.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{13}$$

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

$$WAPE = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{\sum_{i=1}^{n}|y_i|} \tag{15}$$

where $\hat{y}_i$ and y_i represent the predicted value and ground truth data of the value i. n is the number of sample values.

C. Baseline Models

To evaluate the performance of our proposed DyASTGCN model, we compare it with several traditional traffic prediction models and state-of-the-art spatial-temporal traffic prediction models. The baseline models used for comparison are as follows.

- HA: The Historical Average (HA) model predicts traffic flow by taking the average value of historical data.
- SVR: Support Vector Regression (SVR) [49] is a regression algorithm that aims to minimize the discrepancy between the predicted value and a predefined margin,

which is an extension of Support Vector Machines (SVM) for regression tasks.
- LSTM: Long Short-Term Memory (LSTM) [50] is a specialized variant of Recurrent Neural Networks (RNNs) specifically designed to effectively capture and model long-term dependencies in sequential data.
- STGCN: Spatio-Temporal Graph Convolutional Network (STGCN) [47] is proposed to tackle the time series traffic prediction problem by harnessing comprehensive spatial-temporal correlations.
- ASTGCN: Attention-based Spatial-Temporal Graph Convolutional Networks(ASTGCN) [43] is designed for high nonlinearity and complex traffic flow prediction by integrating the spatial-temporal attention mechanism with spatial-temporal convolution.
- Ada-STNet: Adaptive Spatio-Temporal Graph Neural Network(Ada-STNet) [17] developed a graph structure learning component and a dedicated spatial-temporal convolution architecture to capture spatial relationships and temporal dependencies of traffic data.
- STMFGNN: Spatial-Temporal Multifactor Fusion Graph Neural Network (STMFGNN) [51] leverages dynamic similarity and static adjacency graphs for parallel graph convolution, integrating global hidden and local prior knowledge. A gated fusion module adaptively learns dynamic influence weights to capture multiscale spatial dependencies. The model employs gated tanh unit convolution, multireceptive fields, and gated recurrent units for temporal feature extraction, enabling comprehensive traffic flow prediction by considering multiscale factors.

D. Experimental Settings

The experiments are conducted using Google Colab, a cloud-based Python environment. The computing environment included a Tesla L4 GPU with a CUDA version of 12.0. The CPU used was an Intel(R) Core(TM) i9-9900KS clocked at 4 GHz. We implemented all the deep learning models using the PyTorch framework in Python. The models were optimized using the Adam optimizer, with nn.L1Loss() employed as the loss function in PyTorch. This loss function calculates the Mean Absolute Error (MAE) by measuring the average absolute difference between the predicted and actual target values. The hyperparameters for all deep learning models were carefully tuned through a validation set. Specifically, for the DyASTGCN model, we set the model dimension d_{model} to 64, the number of attention heads h to 8, the convolution kernel size to 3, the learning rate is gradually decreased from 0.001 to 0.00001, and batch size is 64.

E. Experimental Results and Discussion

1) Active Mode Spatial Correlations With Weather Influence: Weather conditions, such as precipitation and wind speed, significantly impact cyclists' route choices, leading to changes in traffic patterns and altering the spatial flow dynamics within the network. During extreme weather conditions, cyclists may avoid certain paths in favor of routes that offer more shelter or better drainage. Others might opt for alternative modes of transportation, resulting in notable changes in traffic flow compared to the same time periods under normal weather conditions.

As illustrated in **Fig. 4**, there was heavy precipitation from 16:00 to 17:00 on August 15, 2022, and strong wind from 11:00 to 23:00 on February 18, 2022. The traffic flow patterns during these periods, shown in **Fig. 5** (a) and (c) respectively, demonstrate significant differences when compared to traffic flow patterns during the same time periods on similar weekdays without extreme weather, as depicted in **Fig. 5** (b) and (d). The comparison clearly indicates a decrease in traffic flow during extreme weather conditions.

With the change in traffic flow influenced by weather, the spatial correlations within the traffic network might also shift. However, cyclists' responses to weather changes might not be instantaneous. For instance, if it starts raining, cyclists already on the road might continue their journey until they find suitable shelter, while others might switch to alternative modes of transportation in extreme weather. This lag in response causes temporal shifts in traffic flow, thereby affecting the spatial correlations within the network.

To investigate how weather influences spatial correlations in traffic flow data, we introduce various lags in the weather data to capture the dynamic data-based graph spatial relationships. This approach aligns earlier weather conditions with later traffic flow observations, allowing us to assess if this improves the accuracy of the proposed DyASTGCN model. We conduct three types of experiments to illustrate the lagged effect of different weather factors:

- Precipitation data only: This experiment includes only precipitation data along with traffic flow data to capture dynamic data-based graph spatial correlations for traffic prediction.
- Wind speed data only: This experiment includes only wind speed data along with traffic flow data to capture dynamic data-based graph spatial correlations for traffic prediction.
- Combined precipitation and wind speed data: This experiment includes both precipitation and wind speed data along with traffic flow data to capture dynamic data-based graph spatial correlations for traffic prediction.

As illustrated in **Fig. 6**, our study demonstrates that the DyASTGCN model achieves optimal performance with distinct lag times for precipitation and wind speed data relative to the active mode traffic flow data. Specifically, the model shows the highest accuracy with a 5-minute lag for precipitation data, a 20-minute lag for wind speed data, and a 20-minute lag for the combined precipitation and wind speed data. In particular, the 20-minute lag for the combined precipitation and wind speed data perform the best in all the scenarios.

In the Netherlands, particularly in cities like Rotterdam, cycling is a popular mode of transportation, which is sensible to the weather change. Rain prompts immediate adjustments in cycling routes and behaviors. This rapid response is reflected in the model's optimal performance with a short 5-minute lag for precipitation data. Cyclists often alter their routes or temporarily wait for rain to subside, leading to an immediate

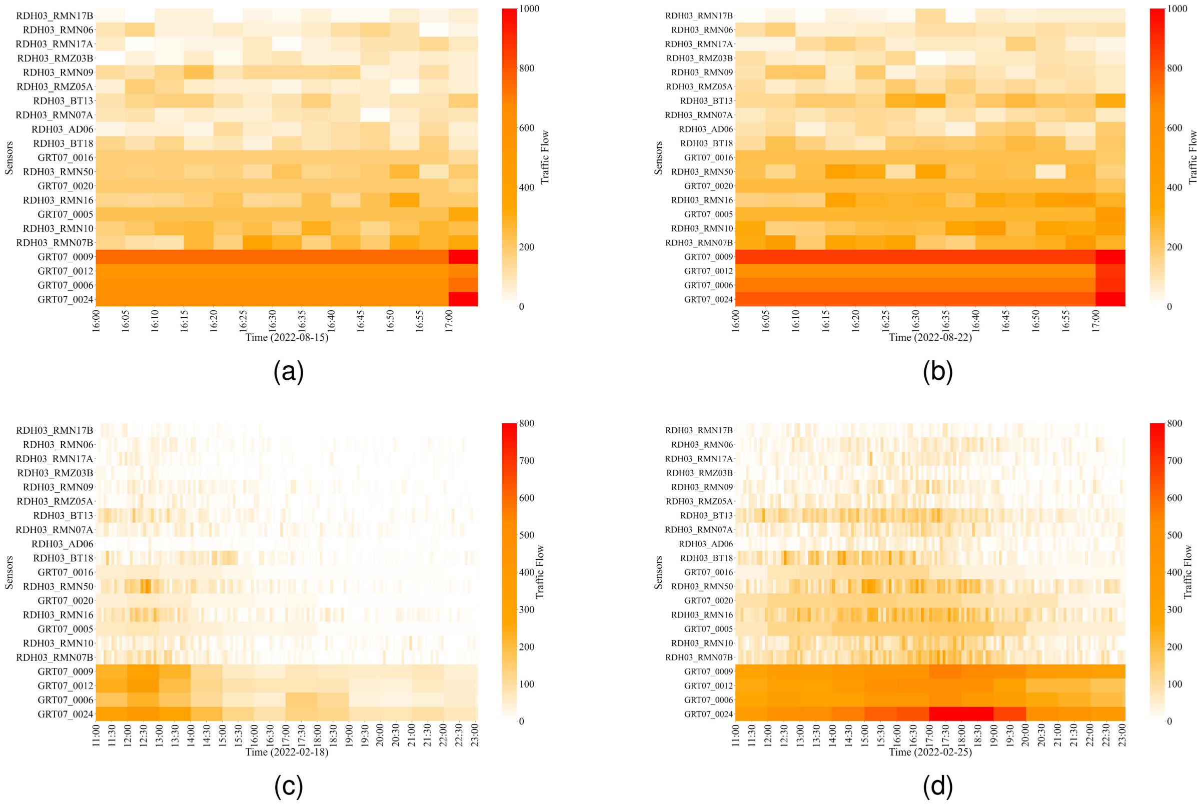


Fig. 5. Traffic flow. (a) Heavy precipitation. (b) No precipitation. (c) Strong wind. (d) Calm wind.

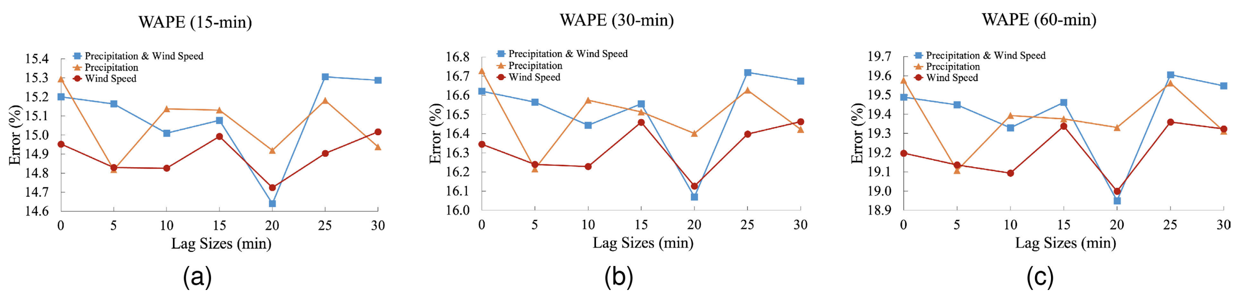


Fig. 6. Performance of DyASTGNN with weather data. (a) WAPE (15-min). (b) WAPE (30-min). (c) WAPE (60-min).

but brief impact on traffic flow patterns. In contrast, wind speed feature has a more gradual impact on cycling behavior. Cyclists may take longer to adjust to windy conditions, resulting in slower speeds or route changes that develop over time. The model's optimal performance with a 20-minute lag for wind speed data reflects this extended adjustment period. Wind affects the ease and safety of cycling, causing sustained changes in cycling behavior, which are captured by the longer lag period. When combining precipitation and wind speed data, the model shows the best performance with a 20-minute lag. This finding indicates that while rain causes immediate changes, the dominant and prolonged impact of wind requires a longer lag period to accurately capture its effect on traffic flow. The interaction between rain and wind creates complex conditions for cyclists, who might wait until conditions improve or adjust more slowly to persistent windy conditions. The 20-minute lag effectively captures the overall impact, particularly the dominant influence of wind, on traffic patterns.

2) Overall Active Mode Traffic Prediction Comparison: **Table I** displays the performance of baseline methods and proposed model, presenting the overall average errors of 15 minutes, 30 minutes, and 60 minutes prediction horizons. Our DyASTGCN model demonstrates superior performance compared to all baseline methods on the dataset of active mode in terms of MAE, RMSE and WAPE, respectively.

Specifically, among traditional statistical methods in the context of time series forecasting, The Historical Average (HA) exhibits the poorest performance when compared to alternative baseline methods. This can be attributed to its reliance only on past data. SVR and LSTM possess the capability to encompass both linear and nonlinear patterns, making them more adept at capturing intricate details within active mode data. However, only considering temporal features of active mode data results in their performance deterioration compared to methods based on graph neural networks. To gain a deeper understanding of traffic patterns, STGCN and ASTGCN leverage graph convolution neural networks to

TABLE I

PERFORMANCE COMPARISON OF MULTI-STEP TRAFFIC PREDICTION

Baselines	**60 min**			**30 min**			**15 min**		
	MAE	RMSE	WAPE	MAE	RMSE	WAPE	MAE	RMSE	WAPE
HA	84.80	143.51	71.02%	84.80	143.51	71.02%	84.80	143.50	71.02%
SVR	40.23	82.36	38.03%	31.47	66.82	29.75%	26.62	58.32	25.16%
LSTM	29.08	65.81	27.49%	22.91	53.72	21.65%	19.34	45.07	18.29%
STGCN	24.82	52.63	23.47%	22.12	46.83	20.91%	19.99	42.24	18.90%
ASTGCN	25.03	53.44	23.67%	21.38	47.46	20.21%	18.79	46.02	17.78%
Ada-STNet	20.12	40.57	19.02%	17.64	37.74	16.68%	16.35	37.05	15.45%
STMFGNN	20.97	38.31	19.83%	19.04	34.82	18.00%	17.96	32.96	16.97%
DyASTGCN	**19.67**	**39.37**	**18.59%**	**16.82**	**35.01**	**15.90%**	**15.42**	**32.75**	**14.58%**

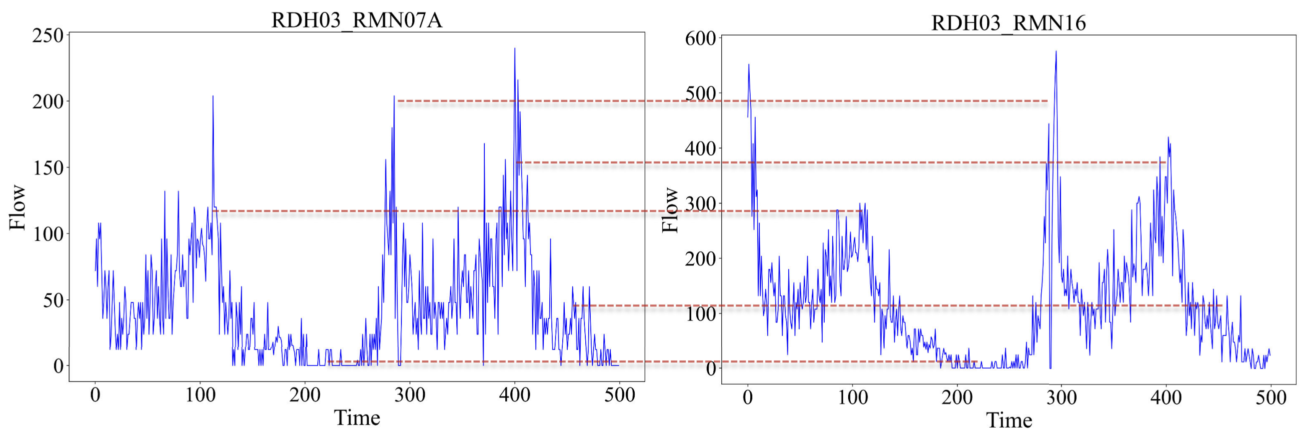


Fig. 7. Bicycle traffic flow distribution.

consider spatial interconnections between traffic components, thus amplifying the precision of predictions. In particular, ASTGCN introduces an attention mechanism into the STGCN model, fostering the capture of dynamic spatial and temporal patterns through an encoder and decoder structure. This augmentation yields superior outcomes on the 60 minutes prediction horizon of active mode traffic prediction. Ada-STNet not only considers temporal dependencies but also incorporates the spatial characteristics of road networks through graph convolution and causal convolution. Additionally, Ada-STNet takes node attributes into account to create dynamic and self-adaptive graph structures, STMFGNN parallelly utilizes dynamic similarity graphs and static adjacency graphs to capture the multiscale spatial dependencies between nodes, surpassing the performance of ASTGCN.

Ada-STNet extracts the node attributes based on a convolution operation, which is well suited to capture relevant features of traffic data. However, in the context of active mode traffic prediction, active mode data might exhibit varying patterns over an hour due to factors such as rush hours, events, or weather changes. Attention mechanism is more adaptable to capturing the attributes of the active mode data and changing relationships between nodes. Therefore, we utilize the attention mechanism to capture the data attribute for graph structure generation over time and capturing temporal and spatial dependencies with graph convolutional neural networks and multi-head self-attention. Furthermore, Ada-STNet fused graph structure with different spatial relationships by summing up all the adjacency matrices, which did not consider the heterogeneity of different adjacency matrices. By contrast, we design a fusion approach to aggregate the matrices properly for active mode traffic prediction. The performance of the prediction model DyASTGCN surpasses Ada-STNet. This outcome highlights the capability of DyASTGCN to effectively capture the variations by considering the influence of weather factors on graph spatial correlations and produce an appropriate adjacency matrix that accurately represents the intricate relationships within the active mode network.

3) The Influence of Spatial Correlations: Bicycle traffic flow often exhibit greater fluctuations compared to car traffic flows due to bicycles being highly sensitive to immediate environmental and situational changes. For instance, cyclists are more affected by weather conditions such as strong winds or rain, which can drastically alter their riding behavior and route choices. Local events or community activities often attract large numbers of cyclists, creating sudden spikes in traffic flow that are less predictable than the more stable patterns observed in car traffic. Furthermore, cyclists frequently make spontaneous decisions to deviate from their routes, such as stopping at local shops or changing paths to avoid congested areas, contributing to the irregular and fluctuating nature of bicycle traffic. As shown in **Fig. 7**, the traffic flow at sensor

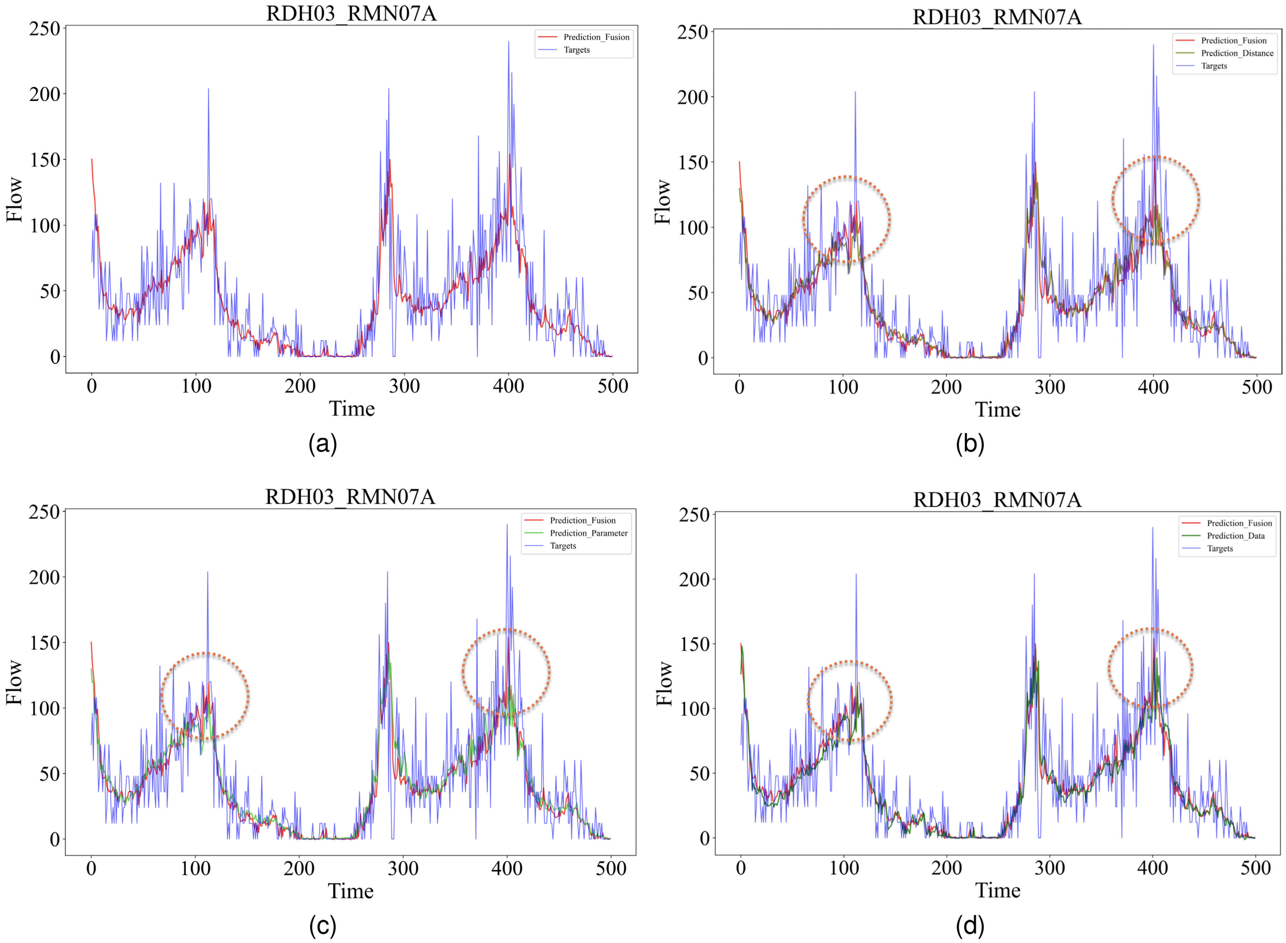


Fig. 8. Bicycle traffic spatial correlations. (a) Optimal fusion-based graph spatial correlations. (b) Distance-based predefined graph spatial correlations. (c) Parameter-based adaptive graph spatial correlations. (d) Dynamic attention data-based graph spatial correlations.

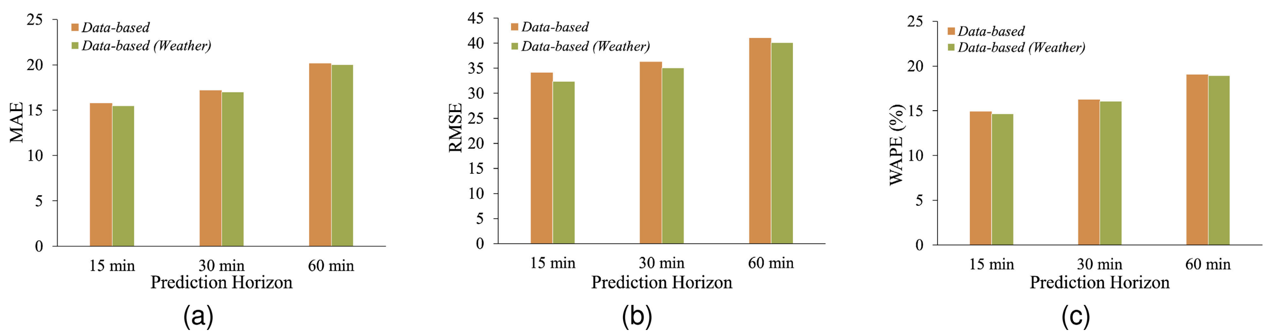


Fig. 9. Graph spatial correlation ablation study. (a) MAE. (b) RMSE. (c) WAPE.

RDH03_RMN16 fluctuates dramatically, with the traffic flow of the previous five minutes differing significantly from the next five minutes. In this case, the local historical traffic flow of this sensor might not be sufficient for accurately predicting future traffic flow, as sudden changes in traffic patterns can occur. However, we observe that at the same time slot, some sensors exhibit similar pattern changes as point out in **Fig. 7**, which could be explained by the interconnected nature of the network where patterns among nodes influence each other.

To explore and capture these spatial correlations for accurate traffic prediction, we introduced various types of spatial correlations: distance-based predefined graph spatial correlations, parameter-based adaptive graph spatial correlations, dynamic attention data-based graph spatial correlations considering weather influences, and optimal fusion-based graph spatial correlations that combine all the above using the proposed fusion approach. The prediction results are shown in **Fig. 8**. **Fig. 8**(a) presents the prediction results of the DyASTGCN model with optimal fusion-based graph spatial correlations. Although this model does not perfectly predict the ground-truth values, it successfully captures spikes in traffic flow to some extent. In comparison, the other models with distance-based predefined graph spatial correlations shown in **Fig. 8** (b), parameter-based adaptive graph spatial correlations shown in **Fig. 8** (c), and dynamic attention data-based graph

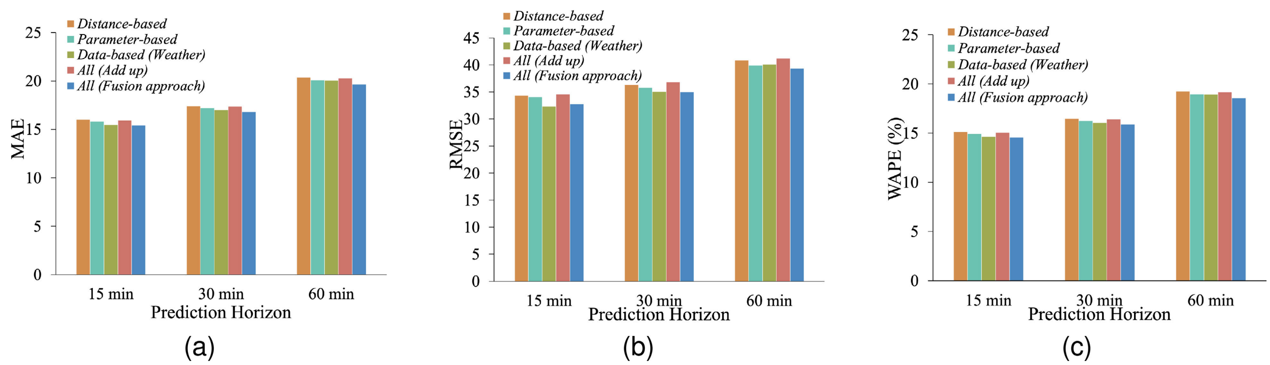


Fig. 10. Fusion approach ablation study. (a) MAE. (b) RMSE. (c) WAPE.

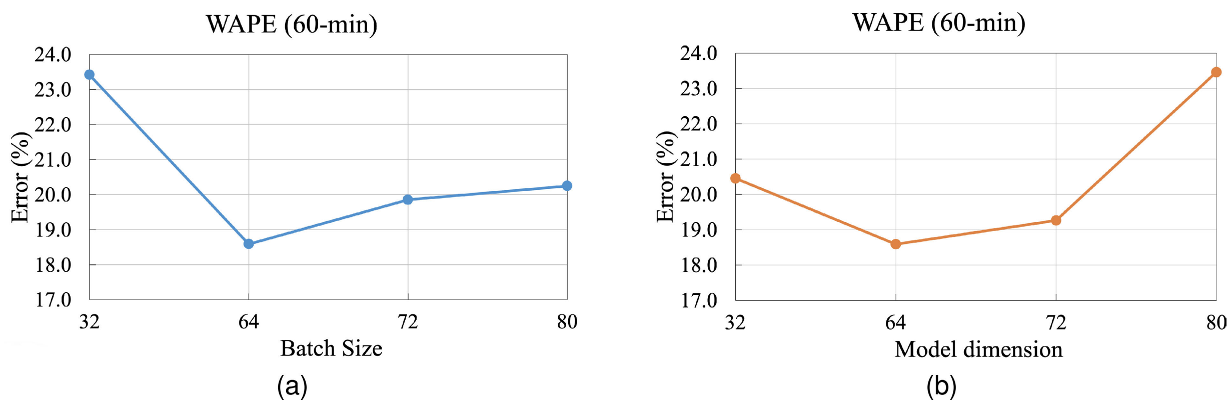


Fig. 11. Hyperparameter analysis. (a) Batch size. (b) Model dimension.

spatial correlations shown in **Fig. 8** (d), demonstrate that the DyASTGCN model with optimal fusion-based graph spatial correlations is more sensitive to fluctuations in bicycle traffic flow.

Distance-based predefined graph spatial correlations can represent geographical spatial correlations based on the road network; however, two sensors close to each other could exhibit dramatically different traffic flows at the same time slot due to differences in road levels or access destinations. Parameter-based adaptive graph spatial correlations capture some hidden spatial correlations among sensors, but these are quite limited. While dynamic attention data-based graph spatial correlations consider traffic flow and weather conditions, they overlook the sensor connections in the actual road network. Therefore, by considering all factors, optimal fusion-based graph spatial correlations more comprehensively represent the spatial correlations among sensors, enabling the capture of fluctuating traffic flow patterns of bicycles.

F. Ablation Study

In order to gain deeper insights into the impact of various components in DyASTGCN, we performed ablation experiments and analyzed the resulting outcomes using the same active mode data as mentioned earlier.

1) Ablation Study of Proposed DyASTGCN: To evaluate the impact of integrating weather data on capturing dynamic attention-based graph spatial correlations in active mode traffic, two experiments were conducted. Our approach involved training a model both with and without the incorporation of weather data while maintaining consistent experimental settings. The primary objective was to assess how effectively our model captured dynamic spatial correlations enhanced by weather information. **Fig. 9** demonstrate that the model incorporating dynamic attention-based graph spatial correlations with weather data outperforms the model that does not consider weather factors. This finding underscores the profound influence of weather conditions on the complex dynamics of active mode traffic networks.

Furthermore, we conducted experiments to evaluate the performance of our proposed heterogeneous graph spatial correlations fusion approach, aimed at combining various types of graph spatial correlations to optimize predictions for active mode traffic networks. As depicted in **Fig. 10**. we compared our fusion approach against several scenarios:

- Distance-based: This model exclusively incorporates predefined graph spatial correlations based on distances.
- Parameter-based: This model solely utilizes adaptive graph spatial correlations derived from parameters.
- Data-based: This model relies solely on dynamic attention data-based graph spatial correlations cooperate with 20-minute lag weather information.
- All (Add up): This model integrates all three types of graph spatial correlations by simply summing them.
- All (Fusion approach): Our proposed approach, where the heterogeneous graph spatial correlations are fused to derive optimal spatial correlations for active mode traffic.

The ablation study revealed that the model employing our heterogeneous graph spatial correlations fusion approach consistently outperformed models that do not integrate various spatial correlations or do not use a systematic approach to harness the utility of diverse spatial correlations. This underscores the critical importance of effectively integrating and leveraging information embedded within diverse spatial correlations for accurate predictions of active mode traffic flow.

2) Hyperparameter Analysis: Hyperparameter tuning is an essential step in optimizing the performance of DyASTGCN. As detailed in the Experimental Settings section, all hyperparameters for the deep learning models were carefully calibrated using a validation set. While many hyperparameters influence model performance, this section highlights batch size and model dimension as illustrative examples. The impact of these hyperparameters on the WAPE error of DyASTGCN is shown in **Fig. 11**, demonstrating that the model achieves optimal performance when the batch size and model dimension are both set to 64.

V. Conclusion

In this study, given the sensitivity of active mode traffic to weather conditions and the complexity of heterogeneous spatial correlations within active mode graph networks, we introduce a Dynamic Attention-based Spatial-Temporal Graph Convolutional Network model (DyASTGCN) for predicting active mode traffic flow. Our model incorporates the influence of weather on traffic graph spatial correlations and proposes a fusion approach to derive optimal spatial correlations that accurately represent active mode traffic dynamics. Experimental results highlight a lag effect of weather on active mode traffic spatial correlations. Specifically, precipitation exhibits a 5-minute lag relative to active mode flow, while mean wind speed shows a 20-minute lag. Including both precipitation and mean wind speed with a 20-minute lag relative to active mode flow yields the best performance compared to above individual scenarios. Our proposed heterogeneous graph spatial correlations fusion approach demonstrates that effectively integrating diverse spatial correlations leads to optimal spatial representations for precise prediction of active mode traffic. This approach ensures that the model captures and utilizes the nuanced interactions between weather factors and traffic dynamics, thereby enhancing prediction accuracy.

Overall, this research underscores the importance of considering weather impacts and leveraging heterogeneous spatial correlations to advance the understanding and prediction of active mode traffic behavior in urban environments. In future research, our aim is to evaluate the model's performance across diverse datasets collected from expansive regions where active mode transportation is prevalent, offering a thorough evaluation of the robustness of the proposed DyASTGCN. Additionally, we plan to explore the influence of various external variables such as individual preferences, road conditions, and other factors on the temporal dynamics of spatial correlations within the active mode traffic. This investigation will broaden our understanding of how these factors interact with and influence the predictive capabilities of our models, thereby enhancing their applicability and robustness in real-world scenarios.

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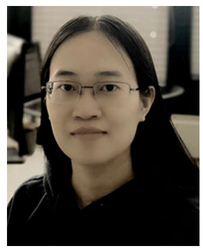

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