Traffic Forecasting in Bogota, Colombia, with Attention Temporal Graph Convolutional Networks (A3T-GCN)

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Abstract

In the context of urban traffic management, advanced Intelligent Transportation Systems (ITS) require flexible, efficient, and accurate traffic prediction models. Such models are essential for enhancing road safety, reducing congestion, and providing assistance to users and city authorities. However, conventional models such as ARIMA, Support Vector Machines, and Artificial Neural Networks (ANN) are constrained in their ability to capture the nonlinearity and spatiotemporal dynamics of traffic data. To address these challenges, this study employs the A3T-GCN model, which integrates attention mechanisms and graph convolutional networks to effectively process traffic data. Specifically, this study focuses on the prediction of traffic flows in Bogotá, a city known for its severe traffic congestion. To adapt the A3T-GCN model to this context, traffic speed data from the Bogotá Open Data Platform was used. The results demonstrate the superior performance of the proposed approach in comparison to conventional ARIMA and ANN models. Notable improvements were observed in RMSE, MAE, accuracy, and explained variance, as well as stability across diverse forecast horizons. Furthermore, the model was employed to simulate a traffic congestion scenario, thereby illustrating its capacity to respond to and adapt to sudden changes in the speed time series. The findings demonstrate the validity and adaptability of the A3T-GCN model for traffic forecasting in Bogotá and highlight its potential as a reliable tool for users and urban management authorities.

Keywords

Deep learning, Spatial dependence, Temporal dependence, Traffic simulation, Latin American urban traffic,

1. Introduction

Nowadays, Intelligent Transport Systems (ITS) play a crucial role in the efficient management of urban traffic, reducing congestion and improving road safety. These systems rely on advanced technologies to collect, process, and analyze real-time traffic data to provide accurate and timely information to users and urban planners [1, 2].

Among the various techniques used for traffic forecasting, statistical and machine learning models stand out. For instance, time series ARIMA models have been widely applied because their efficiency and easy implementation [3]. On the other hand, Vector Autoregressive (VAR) models have been useful for capturing the dynamic interactions between multiple traffic variables by analyzing multivariate time series [4]. However, these models present limitations in capturing the nonlinearities present in traffic data, which has led to the exploration of more sophisticated approaches. In this context, Support Vector Machine (SVM) models have proven to be effective in handling nonlinear relationships through the use of kernel functions [5]. In addition, Artificial Neural Network (ANN) models and more advanced Deep Learning architectures have gained popularity due to their ability to learn and generalize complex patterns in large data sets [6, 7]. Nevertheless, the increasing availability of spatial and temporal data has led to the need for more advanced models that can effectively integrate these dimensions.

A particularly challenging case in the field of traffic forecasting is the city of Bogotá. According to the Traffic Index, Bogotá is the fourth worst city in the world in terms of vehicle traffic [8]. The city's inhabitants lose approximately 126 additional hours per year due to traffic congestion. Although some authors have focused on predicting traffic accidents in the city using conventional techniques, such as the Log-Gaussian Cox process [9] or the probabilistic random walk model [10]. Others, instead, have

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resorted to machine learning models, such as multilayer neural networks [11]. However, there are no specific models for traffic prediction in Bogotá, to the best of the authors knowledge. Therefore, it is essential to develop predictive tools to anticipate traffic patterns and optimize mobility management in the city.

In this paper, we present an innovative approach using the A3T-GCN (Attention Temporal Graph Convolutional Network) model, which combines attention techniques and graph convolutional networks to handle traffic data in a spatio-temporal structure [12]. This model is characterized by its ability to capture the complex dynamics of traffic in road networks, providing a more robust and accurate solution compared to traditional models. In this paper, an A3T-GCN is implemented for traffic prediction in the city of Bogotá.

The paper is organized as follows. Section 2 briefly describes various models used for traffic prediction and discusses their implementations. Section 3 presents the dataset used for the model development, and Section 4 details the steps taken for its preparation and a preliminary exploratory analysis. Section 5 describes the A3T-GCN model and its implementation in the case study. Section 6 presents the results in terms of the training and validation process of the proposed A3T-GCN model, the comparison with ANN and ARIMA models, and the simulation of a traffic congestion scenario. Finally, concluding remarks are given.

2. Related Work

Traffic forecasting models have evolved significantly throughout history, adapting to technological advances and the changing needs of urban planning and traffic management. The following summarizes some of the most common models and their implementation.

2.1. ARIMA

ARIMA models are probabilistic models that describe a variable as a linear function of its past values and random errors. Some extensions, like the seasonal ARIMA models, allow the inclusion of cyclical or seasonal components [3]. T. Alghamdi et al [13] used an ARIMA model to forecast traffic with 2175 observations of traffic flow over a three-month period in a defined study area in California, USA. According to the study, the model must be trained on a large dataset to achieve acceptable accuracy, otherwise the prediction accuracy may be unacceptable. On the other hand, Kumar et al [14] applied a seasonal ARIMA (SARIMA) model in Chennai, India, using only three days of traffic data for a particular road. This approach suggests that useful predictions can be made with less data, depending on the specific characteristics of the time series and the application of the model.

2.2. Autoregressive Vectors (VAR)

The VAR model consists of simultaneous equations that allow the study of how the past value of one variable can affect the present value of other variables and vice versa [15, 16]. This provides a more complete understanding of how variables behave and influence each other. Chandra and Al-Deek [4] presented a VAR model that allows to capture the correlations between upstream and downstream stations for a region in the center of Orlando, Florida, and in this way, the VAR model managed to outperform the ARIMA and SARIMA models.

2.3. Artificial Neural Networks (ANNs) and Deep Learning

Zeng et al. [17] combined an ANN model with a linear ARIMA model to forecast traffic on Guangyuan Highway in Guangzhou, showing that this combination of models can capture different forms of relationships in traffic flow time series data, thereby improving the forecasting performance. On the other hand, Shareef et al. [18] used an ANN model to capture the overlapping restrictions during the COVID-19 pandemic and analyzed their impact on traffic demand. This approach not only effectively modeled these restrictions, but also produced reliable results for other hypothetical scenarios. Finally, Polson and Sokolov [6] present a comparison between a VAR model and a deep learning model for analyzing traffic during events such as a Chicago Bears game and an extreme snowstorm. They develop a framework that combines a linear model with l_1 regularization and a sequence of $tanh$ layers, and find that recent measurements of traffic conditions are more reliable predictors than historical values.

2.4. Support Vector Machines (SVMs)

SVMs are a learning technique used for classification and regression [19]. In the latter case, SVMs formulate a quadratic optimization problem, mapping the nonlinear data to a lower dimension space and performing a linear regression in the transformed space [5]. Theja and Lelitha [19] conducted a comparison of SVMs and ANN models for traffic conditions in India. They found that the SVM models achieved better results for short-term prediction of speed, spatial advance, and volume parameters. It was also observed that SVMs performed better when the training data was of lower quality and quantity [20].

3. Data Understanding

The data used to develop the model were obtained from the *Open Data from the District Mobility Secretariat* website (section *Monitoring*) associated with the Bogotá District Government [21]. These data consist of speed information collected by the Bitcarrier system, an intelligent real-time traffic monitoring and flow technology that uses wireless Wi-Fi and Bluetooth sensors emitted by mobile devices located in Bogotá's road network [21]. The speed data are reported in different segments of the city's most important roads with a frequency of 15 minutes.

The dataset covers monthly periods from February 2019 to November 2022. For the model development, data from 01/06/2022 to 30/06/2022 were used. This decision was made because this dataset had the highest number of records until its last update on 11/11/2022, reaching a total of 2,520,684. The dataset contains 21 variables: 14 numeric, 5 string, and 2 date types. Table 1 shows the most important selected variables for the preparation and modeling process. This information includes date, speed, route, and location data aggregated in fifteen-minute intervals for each segment of the main roads.

Table 1
Most important variable selected

Attribute name	Attribute description	Data type
Inicio	Date and time of measurement	Datetime
Vel_promedio	Average speed measured over the time interval in the road segment	Float
Name_from	Main Road	String
Name_to	Segment information	String
Geomtry_str	Text string with the coordinates of the road segment	String

4. Data Preparation

Thirteen major roadways were selected in a grid that includes streets (east-west/west-east oriented) and avenues (north-south/south-north oriented). These include roadways such as Calle 26, Calle 80, Autopista Norte, and Av. Caracas, among others (Table 2). In this way, the most important segments and their connections were identified for each road. For instance, the segment "Cl80-KR89a; CL80-KR81" –which refers to a segment within Calle 80 with west-east traffic flow from Cl80-KR89a to CL80-KR81–, is connected to the east with the segment "CL80-KR81;CL80-KR76". In total a number of $N = 129$ road segments were selected.

The A3T-GCN model employs a graph representation to process the relationships and characteristics of traffic data. In this graph, nodes represent the selected road segments, and edges represent their connections. An $N \times N$ adjacency matrix is constructed to encapsulate the connection information of the N nodes. The elements in this matrix are set to '1' if the corresponding nodes (specified by the row and column of the matrix) are connected, and '0' if they are not. The graph model is illustrated in Figure in 1 and was generated using Python's NetworkX library. In addition, a matrix of traffic speed attributes is also required with the speed time series (in 15-minute intervals) for each node. Missing values in this data were identified and the NaN values were replaced with the temporal average speed in the corresponding segment, using the SimpleImputer tool from Python's scikit-learn.

Table 2
Selected main roadways and their geographical orientation

Main road	Geographical orientation
Cl. 80	West - East
Av. Caracas	North - South
Cl. 170	West - East
Av. Boyaca	North - South
Cl. 127	West - East
Cl. 26	East - West
Cl. 68	East - West
Cl. 72	East - West
Cl. 100	West - East
Av. 68	South - North
Autopista norte	North - South
Kr. 7	North - South
Av. NQS	South - North

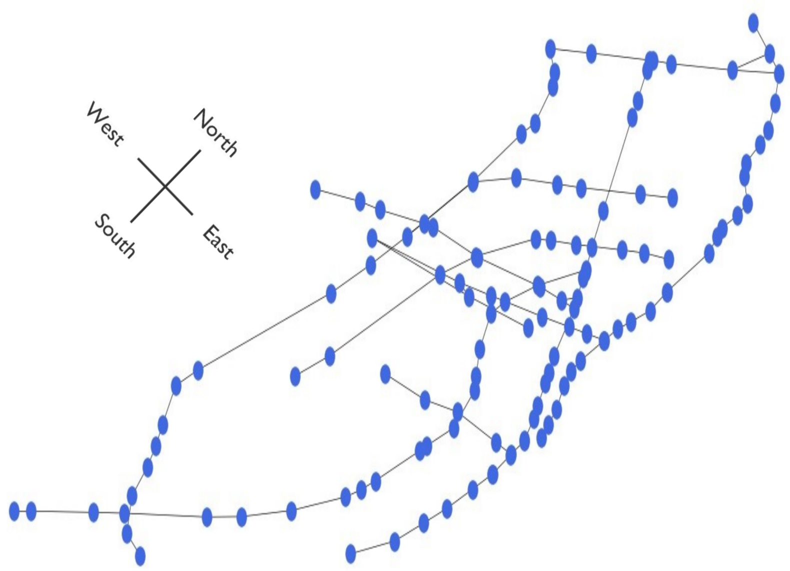

Figure 1: Graph representing the selected segments of roadways (nodes) an their connections (edges) in the city of Bogotá. Along with the traffic speed time series for each node, the graph is the input for the development of the A3TGCN model.

Figure 2 shows the behavior of the average speed on the main roadways. The data show that Autopista Norte and Calle 26 have the highest average speeds, possibly due to their better infrastructure. Conversely, roads such as Calle 100, Calle 72, and Avenida Caracas show lower speeds, which could be attributed to their limited transit space. The average daily speeds in nodes along Calle 80 are depicted in Figure 3. A weekly periodicity is evident in each of the nodes, with Sundays showing speed peaks followed by a noticeable decrease at the beginning of the working week. It is important to highlight that during holidays, such as June 20th and June 27th, there is an increase in speed, suggesting a variation in the typical flow of vehicles on these days. Finally, Figure 4 shows the average speed by hour per node. A clear pattern emerges: during off-peak hours, the speed tends to increase, while during peak hours it decreases significantly, which is the expected behavior within normal conditions.

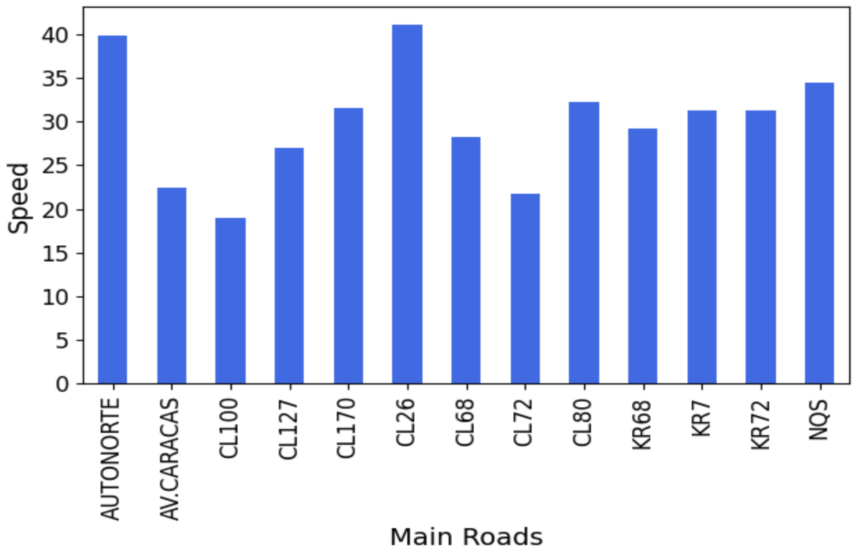

Figure 2: Average speed for main roads.

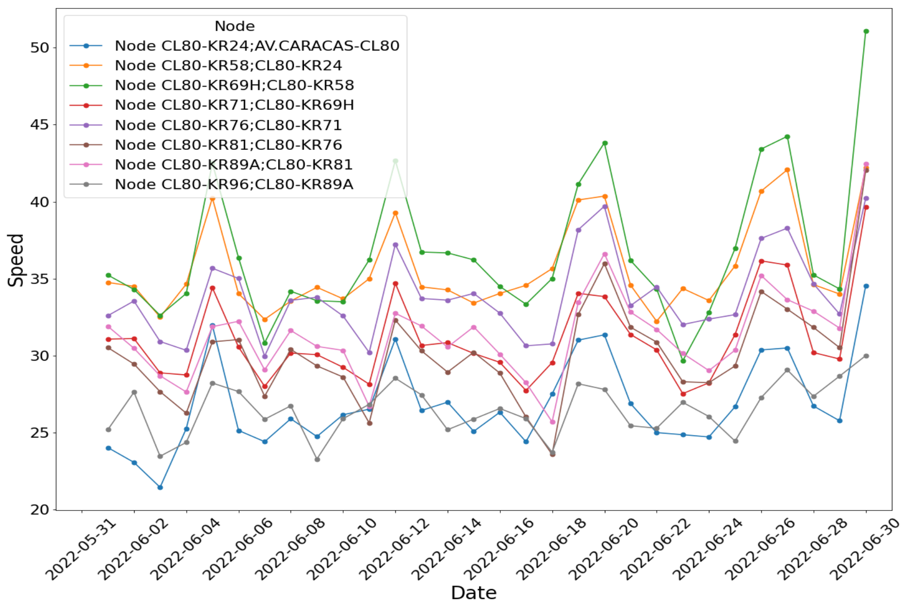

Figure 3: Average daily speed for nodes on cl. 80.

5. Modeling

The A3T-GCN model is an improvement of the T-GCN model that introduces an Attention model [12]. Figure 5 shows the data path through these two constitutive models.

The T-GCN combines a Graph Convolutional Network (GCN) and a Gated Recurrent Unit (GRU). Specifically, the GCN is used to learn complex topological structures to capture spatial dependency,

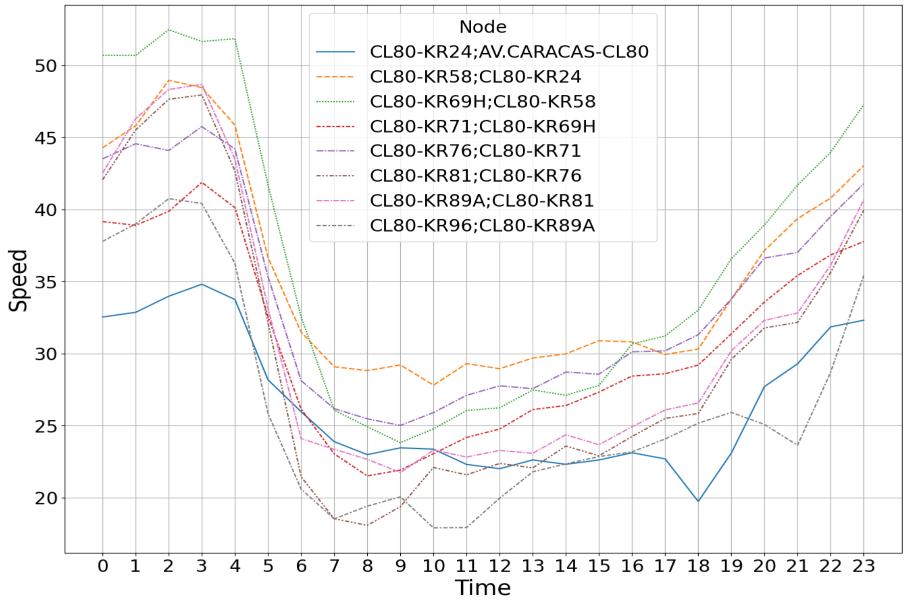

Figure 4: Average hourly speed per day for nodes cl. 80.

based on a graph representation and convolutional operations performed on it [22]. On the other hand, the GRU model is used to learn dynamic changes and to capture time dependence [23]. The update gate controls the degree to which the status information of the previous moment is brought into the current state [24]. The reset gate controls the degree of ignoring the status information of the previous moment [25]. In Figure 5, the input sequences X_{t-n} to X_t are processed by the T-GCN to capture the spatial and temporal dependencies and generate the hidden representations h_{t-n} to h_t.

The second model, the soft attention mechanism, is responsible for reweighting the influence of historical states to capture global variation trends in traffic conditions [23], [12]. This is achieved through a multilayer perception (MLP) that computes the attention scores, $\mathrm{a}_{t-n}, \ldots, \mathrm{a}_t$, which weight the importance of each historical state (see Figure 5). The resulting context vectors are then combined to produce a more accurate prediction based on the relevant information from the historical data.

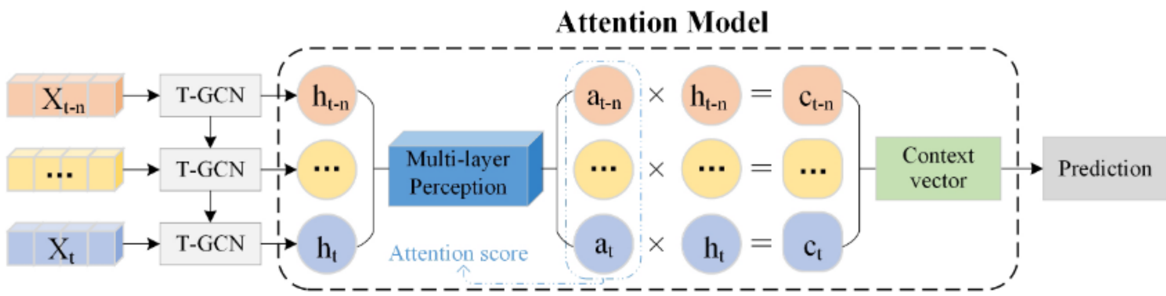

Figure 5: Structure of the A3TG-CN model. Reprinted from "Attention temporal graph convolutional network for traffic forecasting" by Bai Jiandong et al., 2021, *ISPRS International Journal of Geo-Information*, 10(7) [12].

The model was developed using Python libraries such as pandas and numpy for data manipulation, and Pytorch for creating and manipulating tensors, which are the basic structures needed to feed the model. In addition, torch_geometric_temporal, a Pytorch tool, was used to incorporate the A3T-GCN model [26]. For data visualization, matplotlib was used, while validation metrics were computed with scikit-learn. Further development of the model was based on the code of Zhu et al. [27] and Radawn [28], available on GitHub and Kaggle, respectively.

The dataset was divided into a training set (70%), a test set (20%), and a validation set (10%). Traffic was predicted for time windows of 15, 30, 45, and 60 minutes. The results of the model were compared with the best ARIMA model generated by the auto_arima function of the pmdarima library and an ANN model developed with keras library in Python.

6. Results

6.1. Diagnostics for the validation and training phases

Different values of the model's hyperparameters (i.e., learning rate, number of epochs, and number of hidden units) were evaluated. The learning rate was tested at 0.001 and 0.01, with the latter being more effective. The number of epochs was set to 5, as shown in Figure 6, where both training and validation loss plateau beyond this point, indicating that the model stops learning after this value. For the number of hidden units, values of 8, 16, 32, 64, 100, and 128 were tested, with 128 selected for its superior performance. These hyperparameter settings provide a balance between generalization, performance, and computational efficiency.

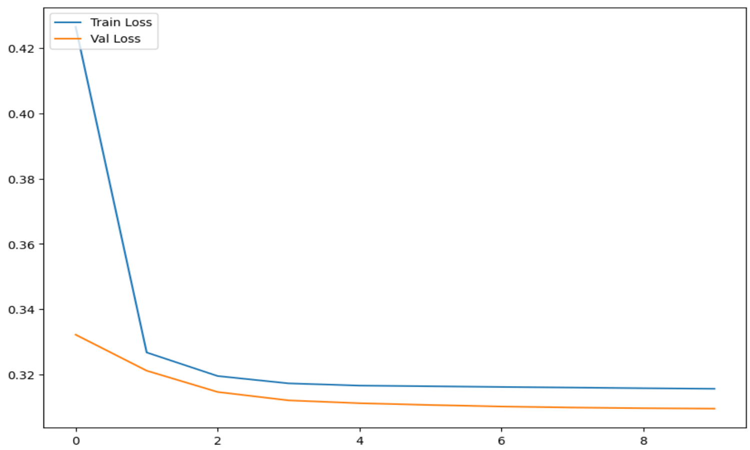

Figure 6: Training loss and validation until 10 epochs.

6.2. Results and comparison

The metrics presented in Table 3 were applied to evaluate the performance of the models, focusing on the discrepancy between the observed speeds and those estimated by the models. Table 4 details the comparative results in the node "CL80-KR81;CL80-KR76" of the speed predictions made by the best ARIMA(1,0,4) model, an ANN model, and the A3T-GCN model for different time windows: 15, 30, 45, and 60 minutes.

As Table 4 shows, predictions of the A3T-GCN model outperform the ARIMA model and the ANN model for all the considered metrics. In particular, Figure 7 illustrates the results for the RMSE. The values of this metric are 18%, 6%, 8%, and 21% lower than those of the ARIMA model for the 15, 30, 45, and 60-minute time windows, respectively, and 63%, 54%, 38%, and 38% lower than the corresponding for the ANN model in the same time horizons. Furthermore, in terms of accuracy, the A3T-GCN model outperforms the ANN model, with 36%, 57%, 38%, and 38% higher values. In addition, the RMSE and accuracy of the A3T-GCN model maintain stable values over the different time horizons. This demonstrates that this model is applicable to both short-term and long-term traffic forecasting tasks. Finally, explained variance values of around 81%-84% and R^2 values close to 0.8 for the A3T-GCN model demonstrate a superior ability over the base models to capture the variability in the observed data.

Table 3
Evaluation metrics applied for the tested models.

Metric	Formula
Root Mean Squared Error	$RMSE = \sqrt{\frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}(y_i^j - \widehat{y_i}^j)^2}$
Mean Absolute Error	$MAE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}\left\|y_i^j - \widehat{y_i}^j\right\|$
Accuracy	$Accuracy = 1 - \frac{\left\|Y-\widehat{Y}\right\|_F}{\|Y\|_F}$
Coefficient of Determination	$R^2 = 1 - \frac{\sum_{j=1}^{M}\sum_{i=1}^{N}(y_i^j - \widehat{y_i}^j)^2}{\sum_{j=1}^{M}\sum_{i=1}^{N}(y_i^j - \overline{Y}^2)}$
Explained Variance Score	$var = 1 - \frac{\left\|Y-\widehat{Y}\right\|_F}{\|Y\|_F}$

Notation: y_i^j and $\widehat{y_i}^j$ are the actual and predicted values at time sample j on node i, respectively. N is the number of nodes on the road. M is the number of temporal samples. Y and $\widehat{Y}$ are the set of y_i^j and $\widehat{y_i}^j$ respectively, and $\overline{Y}$ is the mean of Y. $\|\|\|_F$ represents the Frobenius norm, which calculates the square root of the sum of the absolute squares of the elements of the matrix being evaluated [23].

Table 4
Results of the evaluation metrics of the A3T-GCN model and other standard models on the Bogotá city traffic dataset.

Horizon	Metric	ARIMA	ANN	A3T-GCN
15 minutes	RMSE	5.7883	7.4319	4.7171
	MAE	4.9055	5.4509	3.5764
	Accuracy	-	0.7764	0.8596
	R^2	-	0.4615	0.7896
	var	0.0555	0.35803	0.8389
30 minutes	RMSE	4.9627	10.1425	4.67
	MAE	4.1445	7.999	3.48
	Accuracy	-	0.6948	0.8598
	R^2	-	*	0.7959
	var	0.0555	*	0.8294
45 minutes	RMSE	5.0623	7.4661	4.6431
	MAE	4.4458	5.5184	3.4513
	Accuracy	-	0.7753	0.8604
	R^2	-	0.4565	0.7986
	var	0.0559	0.3727	0.8258
60 minutes	RMSE	5.8815	7.478	4.6582
	MAE	5.2354	5.5265	3.4702
	Accuracy	-	0.775	0.8599
	R^2	-	0.4548	0.7972
	var	*	0.3586	0.8141

Symbol (-) means absence of data for the accuracy metric and R^2. Symbol * means that the values are sufficiently small, indicating poor prediction.

6.3. Forecasted traffic speed for a node

To illustrate the model's output for different forecast horizons (15, 30, 45, and 60 minutes), the predicted traffic speeds for the node "CL80-KR81;CL80-KR76" along Calle 80 from June 25th, 2022 to June 30th, 2022 are presented in Figure 8. As can be observed, the predictions align closely with the actual data for the specified time windows and exhibit acceptable adaptations to sporadic, abrupt changes in the traffic series. Noteworthy, slightly superior results are obtained for the 60-minute time horizon in this node.

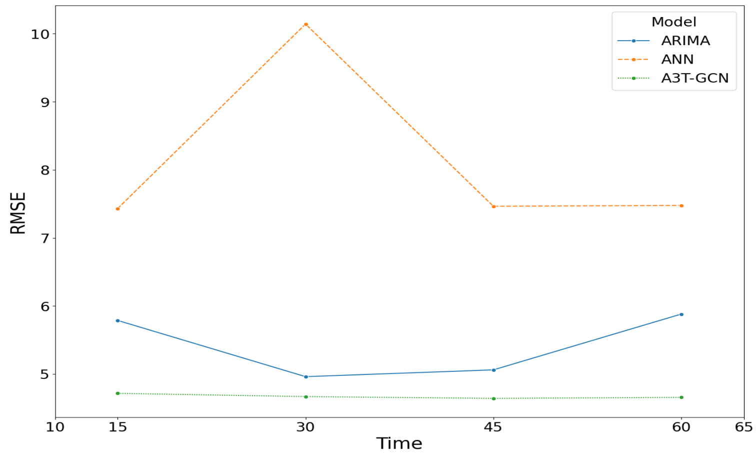

Figure 7: Comparison of RMSE values for the A3T-GCN, ANN and ARIMA model.

6.4. Simulation of a traffic congestion scenario

The trained A3T-GCN model was applied to simulate the impact of traffic congestion in two consecutive nodes along Calle 80, specifically nodes "CL80-KR89A;CL80-KR81" and "CL80-KR81;CL80-KR76". The synthetic data was generated by setting the actual speed measurements at the specified nodes to zero (0) during the 14:30-14:45 and 14:45-15:00 time frames on June 28th, 2022. The impact of congestion on speed prediction was evaluated in the affected nodes, in the preceding (one node) and subsequent nodes (five nodes) along the West-East traffic flow in Calle 80, as well as in the first node of Av. Caracas is connected to Calle 80.

As illustrated in Figure 9, the model demonstrates an ability to adjust its predictions in response to the introduced anomalies. In the modified nodes (top-middle and top-right panels in Figure 9) the new predicted speeds (green lines) exhibit a notable decrease compared to the predicted speeds for the original data (dashed red lines) at the time frames from 14:45 to 15:30. Additionally, a reduction in the speed predictions is observed at the preceding node "CL80-KR96;CL80-KR89A" during a shorter time period from 14:45 to 15:15. Similarly, predicted speeds in the subsequent node, "CL80-KR76;CL80-KR71", show a slight decrease during this same time period. The farthest nodes along Calle 80 and Av. Caracas appears to be unaffected by the simulated congestion. The results demonstrate the A3T-GCN model's capacity to capture the propagation and extent of the effects in the network along and opposite to the traffic flow.

7. Conclusions

In this paper, we successfully adapted the A3T-GCN model for traffic forecasting in the city of Bogotá, Colombia. The preparation, data handling, and model training were essential for the development of the A3T-GCN. The selection of major road segments, its representation via a graph model, and the proper handling of missing values using tools such as SimpleImputer were key aspects that laid a strong foundation for accurate traffic prediction. Given the model's sensitivity to hyperparameters, precise calibration was a crucial step in achieving optimal results.

The application of the A3T-GCN model to this case study demonstrated its superior ability to capture both spatial and temporal dependencies in comparison to the ARIMA and Artificial Neural Network models. The A3T-GCN exhibited superior performance in terms of RMSE and accuracy compared to the other models, while also demonstrating remarkable stability across different prediction horizons, making it suitable for both short- and long-term forecasting. The enhanced performance of the model can be attributed to its capacity to infer information from the entire road network through the graph construction and adapt to dynamic variations and global temporal changes via the GRU and attention mechanisms.

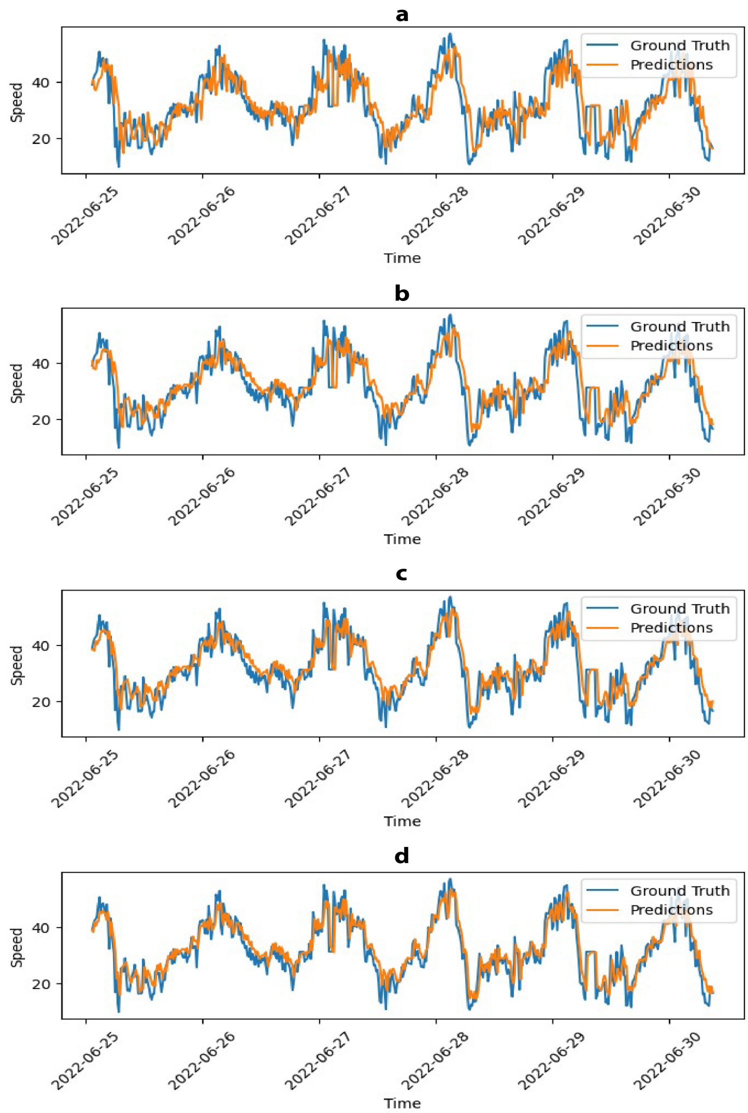

Figure 8: Predicted traffic speed values from the A3T-GCN model in comparison with actual values in node "CL80-KR81;CL80-KR76" for (a) 15 minutes, (b) 30 minutes, (c) 45 minutes, and (d) 60 minutes horizons.

Furthermore, the model demonstrated robust performance in the presence of anomalies, such as sudden traffic congestion, which it successfully simulated. These results indicate that the A3T-GCN model has the potential to serve as a valuable tool for enhancing traffic management in Bogotá, with the capacity to inform and optimize public policies related to mobility and road infrastructure.

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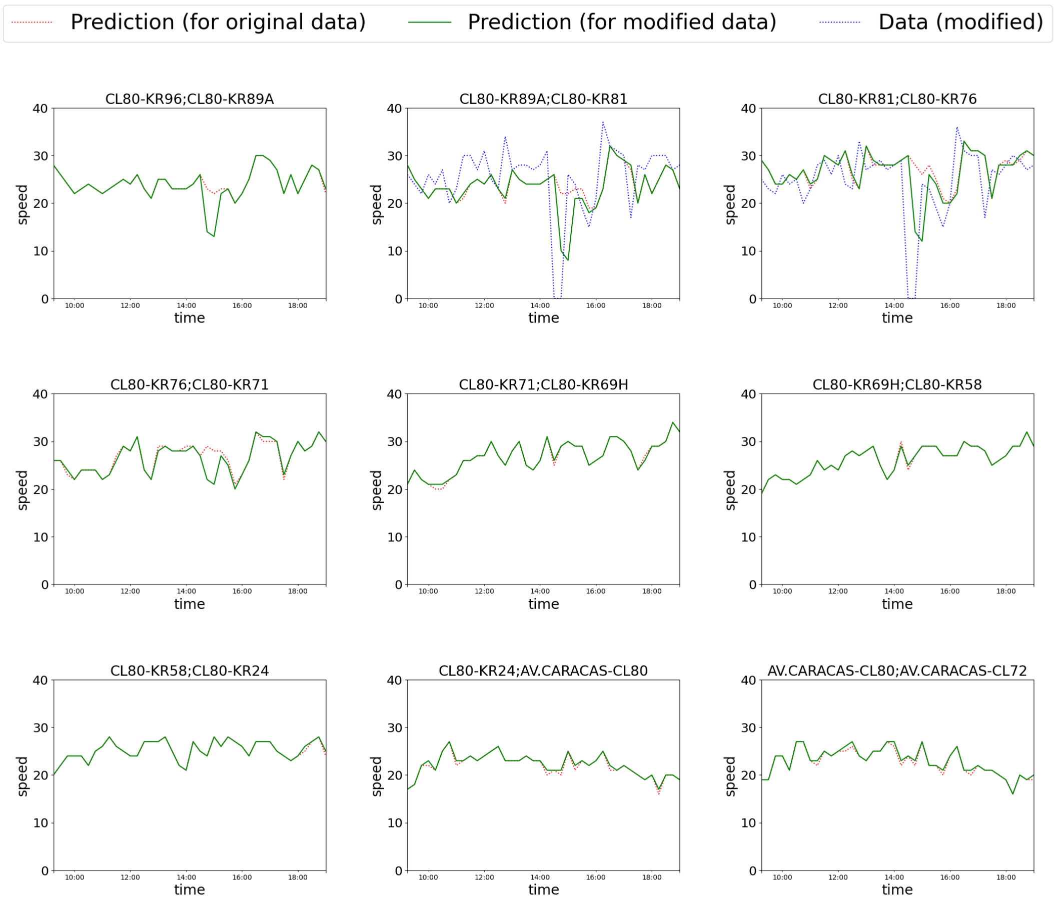

Figure 9: Simulation of traffic speeds from the A3T-GCN model in nodes along Calle 80 and Av. Caracas in response to traffic congestion in two nodes in Calle 80.

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