A Deep Learning Framework for Long-Term Traffic Forecasting on Suburban Freeways with Temporal Instability and Weather Variations

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Research Article

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A Deep Learning Framework for Long-Term Traffic Forecasting on Suburban Freeways with Temporal Instability and Weather Variations

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Abstract

This study proposes a deep learning-based framework for long-term traffic forecasting that incorporates weather variability and temporal instability. Three-hour traffic volumes were predicted using Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) models under various scenarios, including peak and off-peak hours and favourable and adverse weather conditions. Input features included wind speed, temperature,day/night, visibility, rainfall, snow depth, time of day, and holidays. LSTM outperformed MLP during off-peak and favourable conditions due to its temporal memory capabilities, while MLP demonstrated superior adaptability under adverse weather and peak-time conditions. The LSTM model achieved the best performance in off-peak settings, with MAE, RMSE, and MSE values of 0.030, 0.012, and 0.0001, respectively. Holidays, minimum temperature, and day/night were identified as the most influential factors. The results highlight the potential of deep learning models incorporating contextual variables to improve traffic prediction accuracy and support intelligent transportation planning.

Keywords: Deep learning, Big data analytics, Multilayer perceptron algorithm, Adverse weather, Traffic flow prediction

1. Introduction

Transportation is one of the main pillars of social and economic development, influenced by numerous factors, including weather, vehicle types, and road user behavior [1, 2]. Any change in traffic conditions, local or national, can directly impact the country's economy and transportation infrastructure. It has been predicted that, by 2050, the number of vehicles will exceed 2.5 billion globally, indicating a significant increase in demand in the transportation sector [3]. Therefore, accurate prediction of traffic variables and timely notification to users and transportation network managers are key strategies in optimizing transportation systems [4].

Intelligent transportation systems (ITS) provide analytical data and accurate predictions about future traffic conditions, enabling more effective planning and mitigating traffic congestion. Weather conditions are among the most important factors that can significantly affect traffic flow, road safety, and transportation network efficiency [5, 6, 7]. Still, many studies have focused solely on variables such as speed and traffic flow, ignoring the role of the weather [8, 9, 10]. For instance, Lewis et al. (2024) compared different machine learning models for traffic flow prediction using speed, flow rate, and occupancy data. They investigated models such as decision tree, random forest, linear regression, and neural networks, without considering the effect of weather [8]. Some studies that have considered the impact of weather on traffic prediction have focused only on temperature, rainfall, and humidity, mostly neglecting variables such as snow depth, wind speed, and horizontal visibility in the modeling process [11, 12]. A comprehensive understanding of the effects of weather on traffic flow is essential to improving prediction models. Depending on environmental factors, such as altitude, air temperature, rainfall, and wind speed, these effects can vary across geographical areas. For example, vehicle speed reduction is inevitable due to reduced visibility and slippery roads in adverse weather, such as heavy rain, snow, frost, fog, or storms. These variations affect travel safety and reduce the accuracy of traffic prediction models [8, 13].

Choosing the right approach for traffic flow prediction is also of great significance. Some studies have adopted artificial intelligence-based methods for this purpose [11, 14, 15]. Among these, deep learning is one of the most effective techniques [14, 15, 16]. Deep learning-based models have been widely utilized in traffic prediction since they can process big data and identify complex relationships between variables [15, 16, 17, 18]. For example, Raza and Zhong (2016) predicted short-term traffic on a four-lane urban road in Beijing with high accuracy (most of the average errors were < 5-6%, and most 95th percentile errors were <15%) [19]. In a study based on five-minute speed and traffic flow data, Zhao et al. (2017) reported that the long short-term memory

(LSTM) model has higher accuracy in short-term traffic prediction since it can understand long-term temporal dependencies [16].

Despite recent advances in deep learning algorithms, many studies have only examined a particular model without comprehensively comparing the performance of different models under various traffic conditions [11]. Meanwhile, the performance of deep learning models can vary significantly depending on different variables, including peak and off-peak traffic hours and weather conditions. Consequently, the performance of deep learning models under different scenarios must be compared to achieve a more comprehensive analysis. This will provide a more accurate evaluation of different methods and help identify the optimal models for specific conditions.

The present study mainly aimed to propose a comprehensive approach for long-term (three-hour) traffic flow prediction using deep learning algorithms, considering the effects of weather and temporal instability. This study contributes to the literature by comparing the performance of LSTM and multilayer perceptron (MLP) algorithms under different traffic and weather conditions. Unlike previous studies, this study examined common weather variables, such as temperature and rainfall, and less considered factors, such as snow depth, wind speed, and horizontal visibility in traffic flow variation. Besides, the impact of peak and off-peak traffic hours was analyzed separately for the first time. This more comprehensive approach can help improve the effectiveness of predictions and suggest more practical solutions for traffic management.

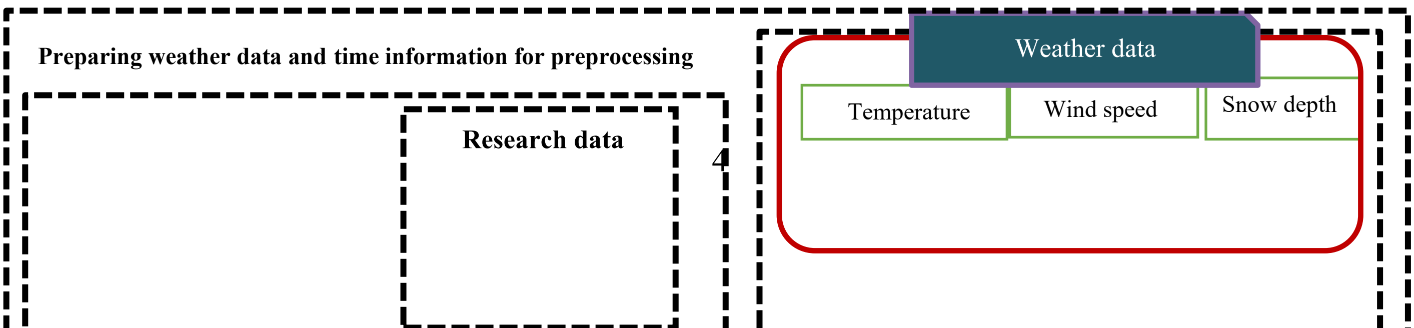
The remainder of this paper introduces the study area, the input data to the LSTM and MLP algorithms, and the proposed method for long-term traffic flow prediction. The architecture of the proposed models based on LSTM and MLP algorithms, evaluation of results, and policy implications are also put forward.

2. Framework and Methodology

The primary approach adopted herein was to propose an intelligent framework based on historical traffic data and temporal instability to predict three-hour traffic flow during peak and off-peak hours, divided by base and adverse weather, and relying on deep learning algorithms. For this purpose, the MLP algorithm was selected due to its outstanding ability to model nonlinear relationships between variables and its adaptability to complex data. Besides, the LSTM algorithm was used as a proposed traffic flow estimation model due to its unique capability to process time series data and maintain long-term information, especially with temporal instability. The proposed models were implemented and compared, divided by peak and off-peak hours and under base and adverse weather conditions. The following 10 models were developed and evaluated:

- M5: Three-hour traffic flow prediction model with the MLP algorithm in comprehensive conditions
- L5: Three-hour traffic flow prediction model with the LSTM algorithm in comprehensive conditions
- M1: Three-hour traffic flow prediction model with the MLP algorithm in adverse weather
- L1: Three-hour traffic flow prediction model with the LSTM algorithm in adverse weather
- M2: Three-hour traffic flow prediction model with the MLP algorithm in base weather
- L2: Three-hour traffic flow prediction model with the LSTM algorithm in base weather
- M4: Three-hour traffic flow prediction model with the LSTM algorithm in peak hours
- L4: Three-hour traffic flow prediction model with the MLP algorithm in peak hours
- M3: Three-hour traffic flow prediction model with the LSTM algorithm in off-peak hours
- L3: Three-hour traffic flow prediction model with the MLP algorithm in off-peak hours

Finally, the effect of each variable on the output of the models was analyzed by gradually eliminating weather variables. Figure 1 displays the proposed research method.



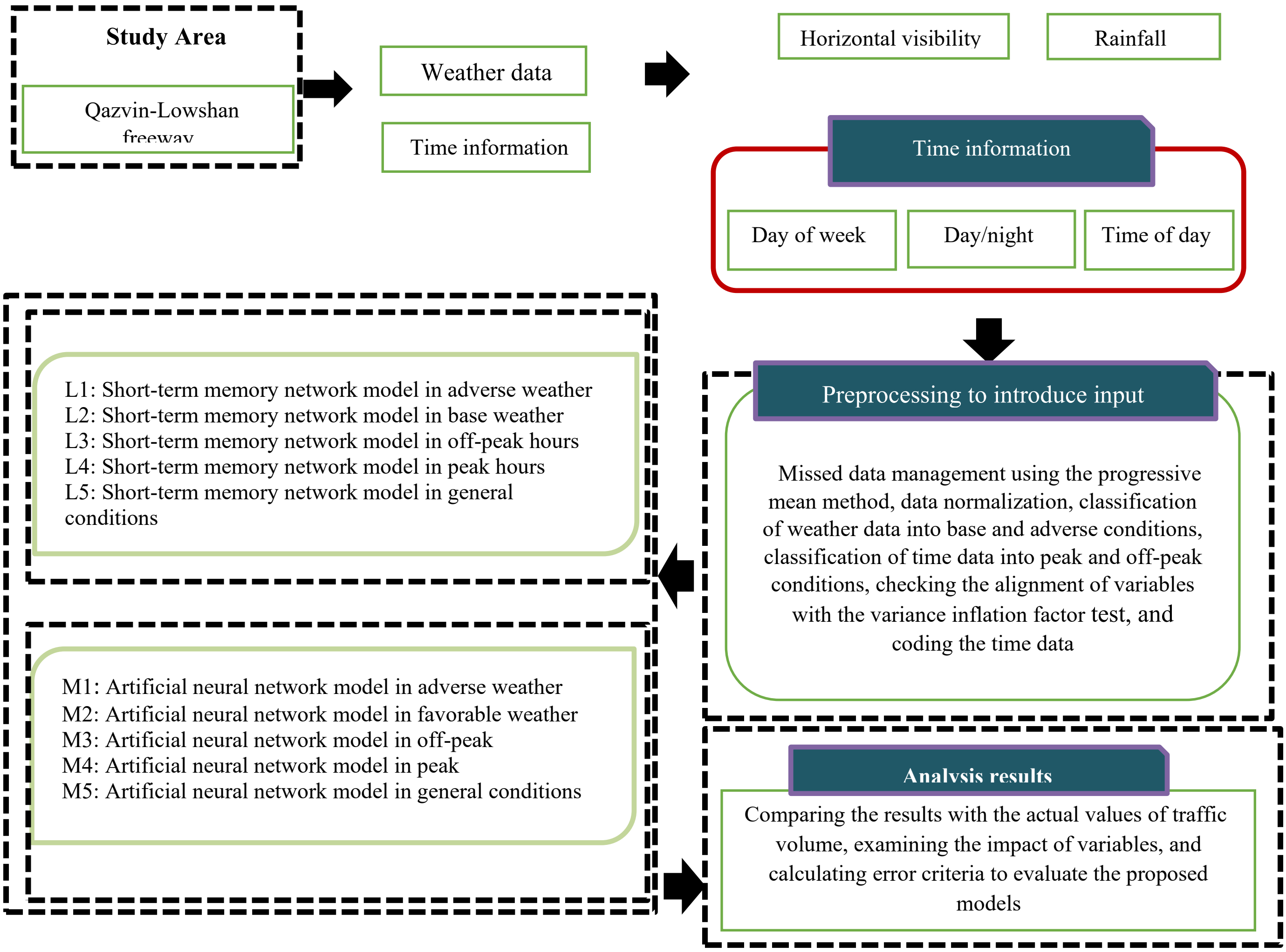


Figure1. Flowchart of the proposed research framework and methodology

As depicted in Figure 1, the first step was to collect the required data. Then, preprocessing was performed to match the weather station data to the traffic flow of light vehicles in the study area. The correlation between the input data was measured using the variance inflation factor (VIF) test. The input data was normalized after combining the weather data with the traffic count. In order to examine the effect of temporal instability on the results of MLP and LSTM algorithms, the weather variables and input time had to be classified (Table 1). Next, the aggregated data were randomly classified into three categories (train, validation, and test). Subsequently, by determining the optimal number of neurons (6) and hidden layers in each algorithm, the data were recalled into the MLP and LSTM models. Finally, the output from MLP and LSTM algorithms was calculated, and evaluation methods, such as mean squared error (MSE), root-mean-square error (RMSE), and mean absolute error (MAE), were calculated. The proposed method was carried out in 10 models, divided into comprehensive, peak, off-peak, base, and adverse conditions so that the performance of the models could be examined more accurately.

2.1. MLP

The MLP model is one of the most fundamental neural models available, and it simulates the information processing of the human brain.

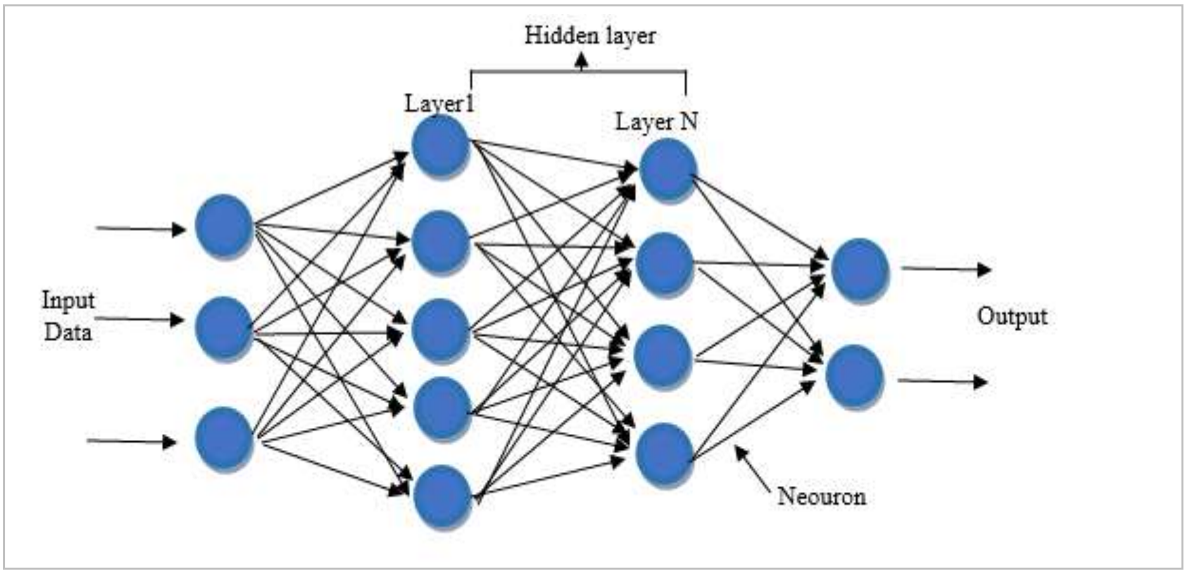


Figure 2. The MLP network structure of the models proposed for three-hour traffic flow prediction (adapted from Maulik et al., 2023)

The most important reasons this algorithm was selected for the current study were its independent decision-making and output. Considering the test phase, this algorithm compares the obtained cases with similar events and generates appropriate responses [20]. The MLP model consists of three main layers: input, hidden layer, and output layer. When data is fed into the network's input layer, the data passes through the input layer. No calculations are performed on the data in this layer, and the input layer is solely responsible for transferring the data to the next layer. The bias of each layer also determines the threshold of a neuron's output. If the sum of the input of a neuron and bias exceeds a certain value, that neuron generates an output; otherwise, the final value obtained by that neuron is zero[21]. The following equation presents the computational processing within each neuron:

$$z = wx + bias \quad (1)$$

where W indicates the network weights and X the network inputs. Each neuron uses this formula for itself.

Thus, the value of z in the above equation is sent to an activation function in the neuron, and the function's output is regarded as the neuron's output. The output value of the neuron is passed to the next layer for calculations.

$$Output = \Phi\,(wx + bias) \quad (2)$$

where Φ is the activation function.

MLP was chosen because it could adapt and learn from train samples. Besides, in MLP, the processing is done cell by cell, and the results are transferred to the next cell after receiving the input; therefore, this algorithm could be effective for three-hour traffic prediction.

2.2. LSTM Network

LSTM networks are deep learning neural networks that retain information over a sequence of data. Unlike traditional neural networks, LSTM has feedback connections that enable it to process the entire data sequence. This makes it highly effective at understanding and predicting patterns in sequential data, such as time series [22].

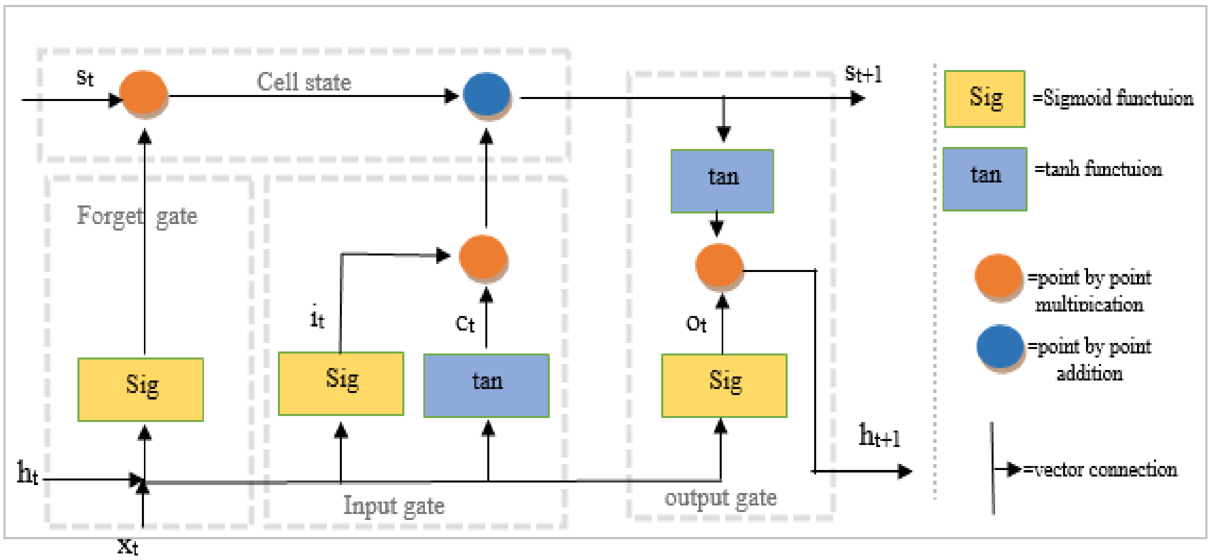


Figure 3. The LSTM network structure of the models proposed for three-hour traffic flow prediction (adapted from Xing et al., 2019)

The recurrent neural network model can consider the dependence of observations; however, the main drawback of this model is that it does not consider long-term dependencies. For example, the traffic status may depend on the traffic status of the previous hour, as well as the traffic status of the same period a year ago. The LSTM memory model, which is a type of deep learning-based recursive neural network model, also considers long-term dependencies. The input to the LSTM memory model includes short-term memory, long-term memory, and some observations in the training dataset. The structure of this model consists of four gates. The input enters the *forgotten gate*, which decides which irrelevant input to discard (Equation 3). The short-term input and some of the trained observations enter the *training gate*, which decides which input should be learned (Equation 4). The outputs enter the *input gate*; the output of this gate is the new long-term memory (Equation 5). Finally, the *output gate* updates the short-term memories and generates the model output (Equation 6).

$$f_t = \delta\ (w_f\ [h_{t-1}\ ,\ x_t] + b_f) \tag{3}$$

$$I_t = \tanh(w_n\ [h_{t-1}\ ,\ x_t] + b_n) \tag{4}$$

$$r_t = I_t + f_t \tag{5}$$

$$o_t = \delta\ (w_o\ [h_{t-1}\ ,\ x_t] + b_o) \tag{6}$$

where f_t, l_t, r_t, and o_t are the forgotten, train, input, and output gates, respectively; h_{t-1} is the output of the previous block; and x_t is the input of gate x at time t. The basic concept of an LSTM network is the cell state and its associated gates. In fact, the cell state acts like a freeway that carries information along the sequence chain. We can think of the cell state as the network's memory. The gates keep the information in the cell state up to date. These gates are different neural networks that decide what information enters the cell state. These gates learn what information should be retained or forgotten during network training [23].

3. Data and Study Area

The studied axis is a part of the Qazvin-Rasht axis with a length of approximately 83 km, which connects Tehran to the north of Iran. The altitude of this mountainous area ranges from 300 to 2394 meters [24]. The freeway passing through the mountainous and foggy areas of Qazvin Province has made it one of Iran's busiest and most critical roads; this demands careful attention to physical and atmospheric factors in transportation network planning [25]. The results of the present study can be generalized to similar freeways in terms of road type and topographic features.

Weather and temporal parameters were studied, including rainfall, minimum and maximum temperature, wind speed, snow depth, time of day, holidays, and day/night. Nine-year meteorological data were collected from the synoptic stations of the Iran Meteorological Organization. This study also utilized light vehicle traffic data recorded over nine years by traffic counters of the Iran Road Maintenance and Transportation Organization.

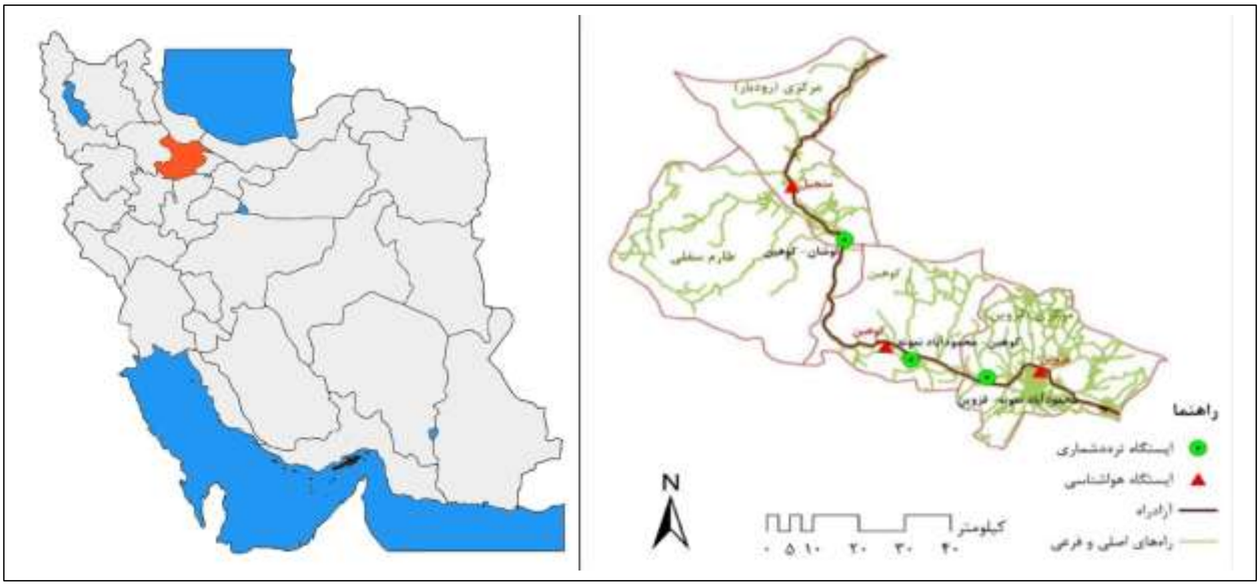


Figure 4. The study area

3.1. Data pre-processing

Data preprocessing included removing outlier data; normalization; combining weather, traffic, and temporal data; adding some temporal variables, such as holidays and day/night; and classifying weather and temporal data into base, adverse, peak, and off-peak categories. First, weather and traffic flow data were combined. Given the small number of synoptic stations close to the study area, the Lowshan-Qazvin freeway was divided into three segments based on the traffic information available on the website of Iran Road Maintenance and Transportation Organization: Lowshan-Kuhin, Kohin-Mahmoudabad Nemooneh, and Mahmoudabad Nemooneh- Qazvin. For each segment, the statistics of the meteorological station closest to the traffic count station of the study area were used to combine the data. Thus, the data from Manjil, Kuhin, and Qazvin meteorological stations were utilized for the Lowshan-Kuhin, Kuhin-Mahmoudabad Nemooneh, and Mahmoudabad Nemooneh-Qazvin sections, respectively. In the next step, the Greenwich Mean Time (GMT) of the weather statistics was converted to the official time of the study area. A significant challenge during data preprocessing was missed data in some time intervals. The progressive mean method was employed to manage missed data. This method works as follows: The missed value is estimated between two adjacent recorded values, such that the new value is as close as possible to the overall trend of the data. This method was selected since it can maintain data continuity and prevent sudden fluctuations in the time series. In addition, the progressive mean method is more accurate in preserving the pattern of data variations than other imputation methods, such as linear interpolation, and prevents unwanted deviations in subsequent analyses.

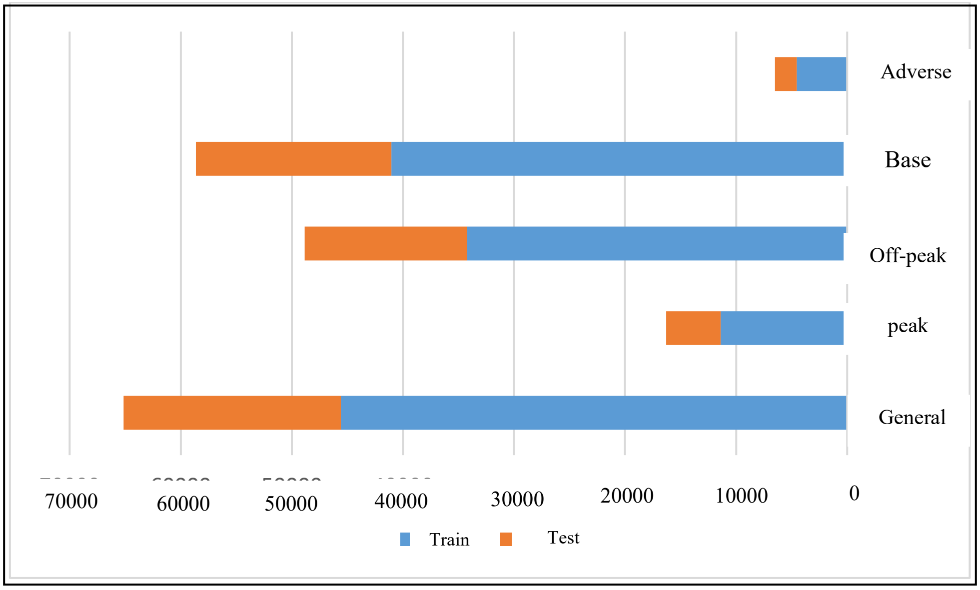


Figure 5. Classification of data into base, adverse, peak, off-peak, and comprehensive conditions

Thus, after data preprocessing and preparation, nine-year (2011-2019) traffic and weather statistics were combined into three separate segments by adding information from the nearest meteorological station. The data used consisted of 65,137 records that were prepared for final analysis after preprocessing. The combined data were divided into base, adverse, peak, and off-peak conditions and then normalized. These classifications were performed based on the thresholds specified in credible studies to properly distinguish base and adverse weather conditions and peak and off-peak traffic periods. Table 1 lists the research variables.

Table 1. Input variables in the dataset

Feature Name	Categories. Thresholds	Type	Unit
Horizontal visibility	>100m (Clear), ≤100m (Low visibility)	Quantitative	Meter
Minimum temperature	>0°C (Above freezing), ≤0°C (Freezing)	Quantitative	°Centigrade
Maximum temperature	>0°C (Above freezing), ≤0°C (Freezing)	Quantitative	°Centigrade
Time of day	Peak (7-10, 16-19), Off-peak	Quantitative	Hour
Holiday	Holiday (0), Working day (1)	Qualitative	-
Wind speed	<10 m.s (Mild), 10-20 m.s (Moderate), >20 m.s (Severe)	Quantitative	Meters.sec

Rainfall	0 mm (No rain), >0 mm (Rain)	Quantitative	Millimeter
Snow depth	0 cm (No snow), >0 cm (Snow)	Quantitative	Centimeter
Day/night	Day (0), Night (1)	Qualitative	-
Season	Spring (0), Fall (1), Winter (2), Summer (3)	Qualitative	-
Road section	Lowshan-Kuhin (1), Kuhin-Mahmoudabad (2), Mahmoudabad-Qazvin (3).	Qualitative	-

The traffic flow at each hour of the day should be examined to identify peak traffic hours. Figure 6 displays the traffic flow variations at each hour of the day, divided by year.

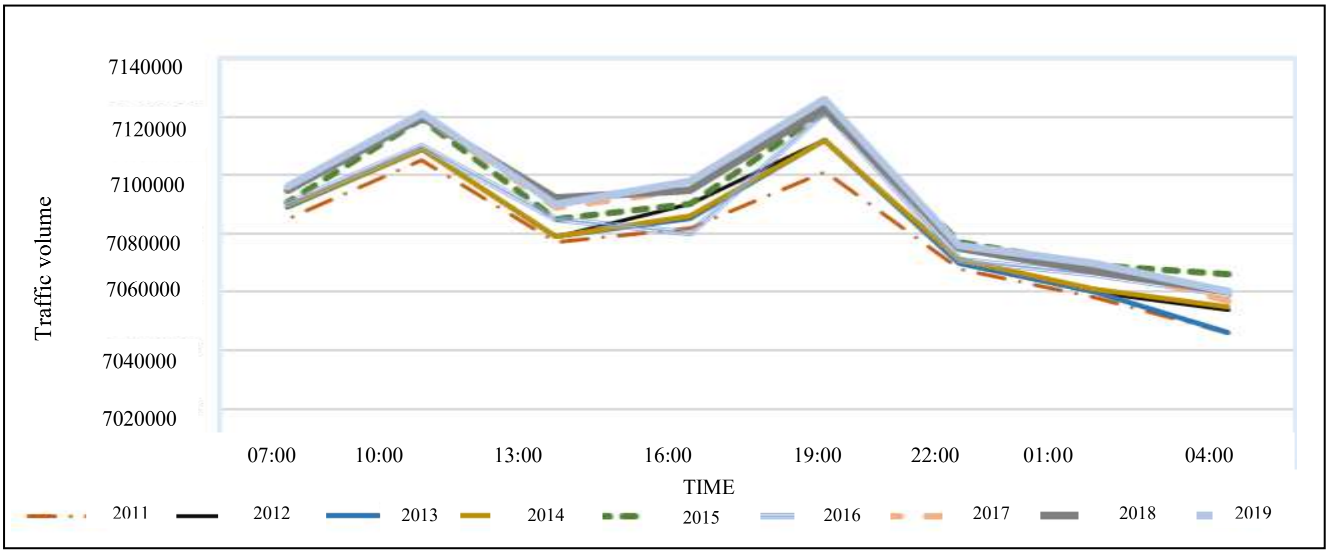


Figure 6. Traffic flow variations at different hours (2011-2019)

Based on this figure, the highest traffic flow in the morning was recorded from 7 to 10 AM on the study area in recent years. The highest traffic flow in the evening was recorded from 4 to 7 PM. Therefore, to investigate the idea of temporal instability resulting from temporal variations in traffic flow patterns, two time periods (7-10 AM and 4-7 PM) were categorized as peak hours and examined in the proposed model.

4. Implementation and results

4.1. Implementing the MLP- and LSTM-Based Models

Determining the number of hidden layers for training an artificial neural network is difficult. The best number of hidden layer was selected through trial and error, multiple modelings, and examining the data training process and each model's error. Eventually, 100 hidden layers were considered for the models based on the LSTM algorithm, and 10 hidden layers for the models based on the MLP algorithm. As shown in Table 2, 70% of the data were used for training and 30% for testing the MLP- and LSTM-based models. Table 2 presents the number of train and test data for each MLP and LSTM-based model.

Table 2. The number of test, validation, and train data in the proposed models

Model name	M5	M4	M3	M2	M1	L5	L4	L3	L2	L1
Training	39082	14253	31342	41043	4552	39082	14253	31342	41043	4552
Test	26054	6108	13433	17590	1951	26054	6108	13433	17590	1951
Data sample	65137	20362	44775	58634	6504	65137	20362	44775	58634	6504

The data from four years were selected as training data in M5 and L5 models. In the other models, it was not possible to determine the year in the test and training data due to data filtering.

Based on empirical rules, the number of neurons is usually half the value of the input data [20]. The activation function for the hidden layers was determined as a Sigmoid function, and the training type was determined as batch since batch data were utilized.

4.2. Evaluation metrics

MSE, RMSE, and MAE validation metrics were employed to evaluate the traffic flow prediction results and the degree of agreement between the findings and the actual three-hour traffic flow values.

$$\text{MAE} = \frac{1}{n} \sum | \hat{\varphi}_i - \varphi_i | \tag{7}$$

$$\text{MSE} = \frac{1}{n} \sum (\hat{\varphi}_i - \varphi_i)^2 \qquad (8)$$

where $\hat{\varphi}_i$ is the predicted data, φ_i is the actual and recorded data, and n represents the number of data. MAE, RMSE, and MSE are highly sensitive to raw traffic data, so they were suitable options for validating the prediction results.

4.3. Results of the LSTM- and MLP-Based Models

To evaluate the performance of the proposed models, the results of their implementation were compared with the actual traffic flow values recorded by traffic counters. The results of all models were also compared with each other to identify the best model. Before using the models for real-world applications, it is essential to carefully evaluate them. As mentioned in the research methodology section, 10 models based on the MLP and LSTM algorithms were implemented for different conditions, including comprehensive, peak, off-peak, base, and adverse conditions. As displayed in Figure 2, the results of each proposed model were compared with the actual traffic flow data. In the comprehensive, off-peak, and base conditions, the LSTM algorithm outperformed the MLP. This performance improvement was due to the ability of LSTM to analyze long-term dependencies in temporal data. In contrast, in peak and adverse conditions, the MLP algorithm outperformed; this indicates that MLP is superior when there are sudden changes in the data since it can learn nonlinear and complex relationships.

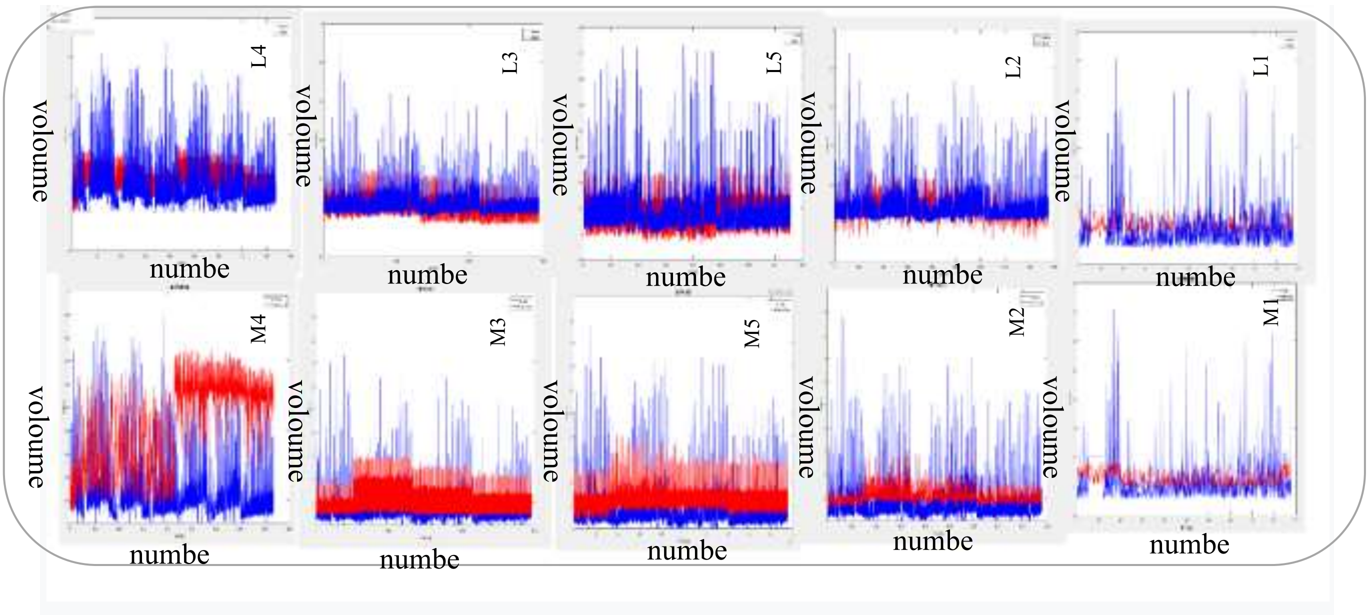


Figure7. Results of the proposed MLP and LSTM models

When weather variables were stable, LSTM outperformed due to its memory structure. However, in unstable conditions, MLP outperformed better due to its lack of dependence on past temporal data. Table 4 presents the evaluation metrics for all the proposed models. Overall, LSTM algorithms were associated with lower error and performed better than MLP.

Table 3. Results of evaluation metrics for the proposed models based on LSTM and MLP algorithms in test conditions

Model Name	MAE	MSE	RMSE
M1	0.0045	0.0003	0.017
M2	0.045	0.0003	0.014
M3	0.050	0.0006	0.025
M4	0.95	0.017	0.138
M5	0.070	0.008	0.089
L1	0.006	0.0005	0.022
L2	0.040	0.0002	0.055
L3	0.030	0.0001	0.012
L4	0.097	0.019	0.141
L5	0.065	0.007	0.084

First, the proposed models based on LSTM and MLP algorithms were examined in comprehensive, peak, off-peak, base, and adverse conditions. Subsequently, the impact of input variables on long-term traffic flow prediction was assessed in each algorithm that outperformed.

Based on Table 4, the MLP algorithm showed superior performance in adverse weather compared to the LSTM algorithm. In adverse weather, traffic patterns may have sudden and unpredictable changes that appear as noise in the data. Due to its recursive structure, the LSTM algorithm may consider this noise as temporal information, which decreases the algorithm's efficiency. The MLP algorithm may be less affected by this noise due to its lack of dependence on past temporal data and may perform better when sudden changes occur.

The LSTM algorithm performed better than the MLP algorithm in base weather conditions. The weather is more stable in base conditions, and traffic follows regular temporal patterns. The LSTM algorithm can learn these temporal patterns well by using its internal memory and, thus, make appropriate predictions. However, due to its feed-forward structure, the MLP algorithm has limitations in modeling time dependencies and may not perform well for data with long-term time dependencies.

The LSTM algorithm outperformed the MLP algorithm in off-peak conditions due to its ability to learn long-term time patterns. In contrast, the performance of the MLP algorithm in peak conditions was superior to the LSTM algorithm. The MLP algorithm is suitable for modeling nonlinear relationships between inputs and outputs. Therefore, in peak conditions with many sudden changes in traffic flow, this algorithm was superior to the LSTM algorithm due to its simple structure and lack of dependence on past temporal data. Finally, the LSTM algorithm performed better than the MLP algorithm in comprehensive conditions due to its gate-based structure and consideration of long-term data dependence.

Understanding the performance of LSTM and MLP algorithms in traffic flow prediction in temporal instability caused by comprehensive, peak, off-peak, base, and adverse conditions provides a more complete understanding of traffic flow patterns, which can lead to timely and effective decisions in traffic management. Recognizing the variables affecting traffic flow prediction is particularly important since they can directly improve traffic management, reduce traffic, and save time and resources.

Based on Table 5, holidays, day/night, and minimum temperature were the most influential variables in long-term traffic flow prediction in temporal instability conditions caused by comprehensive, peak, off-peak, base, and adverse conditions. Holiday was the most influential variable in long-term traffic flow prediction. Traffic flow on suburban freeways may change significantly during holidays. This indicates that planning for traffic management should be different on holidays compared to regular days. On the other hand, traffic increases on cold days due to low temperatures and frost. This suggests that weather conditions can change traffic patterns. In peak hours, the time of day significantly impacted long-term traffic flow prediction in addition to holidays, day/night, and minimum temperature. People use vehicles more at certain times of day, such as the beginning or end of working hours. These recurring behaviors make the time of day a strong predictor, demonstrating that human behavior is strongly influenced by the time of day and that these behaviors directly affect traffic flow. Given the impact of time on traffic flow during peak hours, the effect of this variable can be used to optimize traffic management. For instance, notifying drivers to avoid entering high-traffic areas at certain times can help manage the transportation system more effectively. Identifying variables that affect long-term traffic flow prediction is a powerful tool for improving traffic management. This information helps decision-makers offer effective solutions to reduce traffic, enhance the infrastructure, and improve road safety using advanced analytics.

Table 4. Performance evaluation of input variables to the models based on LSTM and MLP algorithms

Evaluation of variables in superior models															
	M1			**L2**			**L3**			**M4**			**L5**		
Variable name	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE
Wind speed	0.094	0.074	0.008	0.097	0.007	0.009	0.124	0.104	0.015	0.150	0.107	0.02	0.105	0.077	0.011
Rainfall	0.092	0.072	0.008	0.103	0.085	0.010	0.091	0.068	0.008	0.133	0.086	0.017	0.093	0.073	0.073
Snow depth	0.082	0.06	0.006	0.088	0.067	0.007	0.091	0.065	0.008	0.132	0.088	0.017	0.085	0.070	0.007
Holiday	0.105	0.08	0.011	0.090	0.007	0.008	0.102	0.082	0.001	0.133	0.088	0.017	0.087	0.059	0.007
Minimum temperature	0.083	0.05	0.006	0.100	0.008	0.001	0.110	0.082	0.001	0.133	0.088	0.017	0.1048	0.089	0.001
Maximum temperature	0.084	0.05	0.05	0.092	0.072	0.008	0.112	0.090	0.001	0.133	0.096	0.017	0.090	0.065	0.008
horizontal visibility	0.086	0.05	0.007	0.097	0.078	0.009	0.099	0.074	0.009	0.163	0.150	0.02	0.093	0.075	0.008
Day/night	0.08	0.06	0.007	0.097	0.078	0.009	0.98	0.076	0.0005	0.124	0.088	0.015	0.111	0.091	0.012
Time of day	0.08	0.06	0.007	0.10	0.081	0.001	0.081	0.050	0.006	0.126	0.090	0.015	0.075	0.004	0.005

5. Policy Implications

The findings of this study revealed that traffic flow prediction, relying on changes in environmental and temporal variables, such as horizontal visibility, wind speed, holidays, day/night, time of day, and temperature (minimum and maximum), can help improve traffic management and enhance road safety. Based on the results in Table 4, holidays, minimum temperature, and day/night were identified as the most influential factors in traffic flow prediction. Accordingly, the following recommendations are made to improve traffic management and promote safety:

Given the superior performance of the MLP model in traffic flow prediction in adverse weather, it is recommended that this model be used to predict traffic flow on rainy and snowy days, or days with reduced horizontal visibility, more accurately. Due to its outstanding ability to learn nonlinear and complex relationships between traffic and weather variables, the MLP model can make more accurate predictions than traditional models. These predictions can help traffic managers and planners take appropriate measures by predicting an increase or decrease in traffic flow under specific conditions [26, 27].

When there is reduced horizontal visibility, traffic management systems can adjust traffic lights or suggest alternative routes to drivers by predicting increased traffic in specific areas to avoid heavy traffic jams. Moreover, given the ability of the MLP model to predict traffic flow during peak hours, solutions such as increasing route capacity, dedicating lanes for public vehicles, and imposing temporary traffic restrictions can help improve traffic management during these periods. During peak hours, intelligent traffic light control systems can be utilized to reduce traffic and improve vehicle flow using predicted data [28].

In addition, considering the significant impact of variables such as public holidays, minimum daily temperatures, and differences in traffic behaviors during day and night, these factors should be specifically considered in traffic flow prediction models. On holidays and at night, when traffic flow is more likely to increase due to social or recreational activities, traffic management systems can predict this increase in volume and take necessary measures, such as increasing route capacity or notifying drivers. Furthermore, when the minimum air temperature drops significantly on cold days, traffic flow prediction can help traffic planners take necessary measures to manage traffic in frost conditions. Notifying drivers about the possibility of increased traffic in certain areas or suggesting alternative routes can help reduce traffic and improve vehicle flow. Warning systems can also inform drivers of predicted traffic conditions through text messages, variable message signs, or mobile applications. Finally, using traffic flow prediction models can help improve traffic management in different weather and temporal conditions and provide accurate forecasts, enabling better planning and traffic reduction.

6. Conclusion

Weather is an influential factor in traffic flow prediction. Weather conditions have wide-ranging effects on driver behavior, transportation infrastructure efficiency, and traffic flow; therefore, examining traffic prediction in various weather conditions is important. Understanding traffic flow prediction methods and techniques is essential for managing the transportation system.

A literature review showed that studies into the effects of weather on traffic flow prediction had often considered a limited number of weather variables. Given the ability of deep learning algorithms to analyze big data and examine data sequences, LSTM and MLP algorithms could play an effective role in long-term traffic flow prediction. Therefore, this study aimed to examine the performance of LSTM and MLP algorithms in long-term traffic flow prediction. Then, by classifying weather and temporal data, these two algorithms were implemented in unstable weather and temporal conditions. This study was conducted on 10 proposed models based on LSTM and MLP algorithms for peak, off-peak, base, and adverse weather conditions.

Based on the findings, the best performance among the 10 proposed models belonged to the model based on the LSTM algorithm in off-peak conditions, with MAE, RMSE, and MSE values recorded as 0.030, 0.012, and 0.0001, respectively. In adverse weather, the performance of the MLP algorithm was superior to the LSTM algorithm. In base weather conditions, the LSTM algorithm outperformed the MLP algorithm. In peak traffic hours, the performance of the MLP algorithm was better than that of the LSTM algorithm. In comprehensive and non-peak conditions, the LSTM algorithm outperformed the MLP algorithm.

The findings revealed that using deep learning algorithms for long-term traffic flow prediction by considering weather parameters can provide a more accurate and complete understanding of traffic patterns. Holidays, day/night, and minimum temperature were the most influential variables in three-hour traffic flow prediction.

Weather instability plays a determining role in traffic flow prediction. Weather changes, such as temperature drops, precipitation, and storms, can significantly affect driver behavior and traffic patterns; thus, identifying influential variables, such as holidays, day/night, and minimum temperature, as key factors in traffic prediction allows for more accurate modeling and more efficient planning. By considering weather instability, these variables help improve prediction accuracy and help manage traffic more effectively in variable weather conditions.

The present study offers an innovative approach to deep learning algorithms that can provide valuable information to the Iran Road Maintenance & Transportation Organization. Researchers are advised to examine the performance of deep learning algorithms during the COVID-19 pandemic. Besides, since the area studied in this research was a freeway, changes in traffic patterns should be investigated in an urban setting based on weather data.

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