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A Comparative Study of Different Time Series Forecasting Methods for Predicting Traffic Flow and Congestion Levels in Urban Networks

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Abstract

This research Traffic congestion is a growing problem in urban areas, leading to significant economic and environmental costs. Accurate prediction of traffic flow and congestion levels can help transportation planners and policymakers make informed decisions to alleviate congestion and improve traffic efficiency. Time series methods have been widely used for traffic prediction due to their ability to capture temporal dependencies and patterns in the data. This study aims to evaluate the performance of different time series methods for predicting traffic flow and congestion levels in urban networks. Five commonly used methods were examined, including Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Vector Autoregression (VAR), Exponential Smoothing (ETS), and Long Short-Term Memory (LSTM). The strengths and limitations of each method were analyzed based on their ability to capture complex patterns, handle non-stationary data, and provide a measure of forecast uncertainty. Results showed that ARIMA and SARIMA can effectively model seasonal patterns and provide forecast uncertainty, but may struggle with capturing complex nonlinear relationships and sudden disruptions in traffic flow. VAR can capture interdependencies between road segments, but assumes linear relationships and requires a large amount of data. ETS can handle missing data and model trends and seasonality, but also assumes stationary data and may struggle with sudden changes in traffic flow. Finally, LSTM can capture complex nonlinear relationships and handle multiple input variables and time lags, but requires a large amount of data to train and can be computationally expensive.

Keywords: *Congestion, Flow, Methods, Prediction, Traffic, Urban*

Introduction

Traffic congestion is a pervasive problem that affects both developing and developed cities worldwide. It is a complex phenomenon that arises from several factors, including population growth, urbanization, inadequate infrastructure, and a lack of efficient public transportation systems [1], [2]. The economic costs of traffic congestion are enormous and can negatively impact a city's productivity and competitiveness. Traffic congestion can lead to increased fuel consumption, higher operating costs for businesses, decreased reliability in vehicular networks [3], [4], and reduced employee productivity. Moreover, traffic congestion can also have adverse environmental consequences, contributing to air pollution and greenhouse gas emissions. To address the challenges posed by traffic congestion, governments and transportation agencies worldwide are investing in new technologies to enhance traffic flow and travel efficiency. These include intelligent transportation systems (ITS), traffic management centers, advanced traffic signal control systems, and integrated corridor management systems. For instance, ITS uses real-time data to provide travelers with up-to-date information about traffic congestion, travel times, and alternate routes.

Traffic flow prediction refers to estimating the number of vehicles expected to pass through a given roadway segment in a given time period. There are several techniques for predicting traffic flow, including statistical models, artificial neural networks, and machine learning algorithms. Congestion level prediction refers to estimating the degree of traffic congestion in a given roadway segment. This prediction helps transportation planners and operators identify congested roadways and take appropriate measures to alleviate congestion. There are several techniques for predicting congestion levels, including data-driven approaches, simulation models, and hybrid models [5].

Data-driven approaches use historical traffic data and other input features like weather, time of day, and road network characteristics to predict congestion levels [6], [7]. These approaches include statistical models, ANNs, and machine learning algorithms.

Simulation models simulate traffic flow using mathematical models based on the fundamental principles of traffic flow. volume, speed, and density, along with external factors like weather conditions and road network characteristics, to predict congestion levels [8]. Microsimulation models, mesoscopic models, and macroscopic models are some of the simulation models used for predicting congestion levels. Hybrid models combine data-driven approaches and simulation models to predict congestion levels. These models use historical traffic data and other input features to initialize simulation models and improve the accuracy of congestion level predictions.

For transportation planners and operators, accurate predictions help optimize traffic management strategies and improve the efficiency of the transportation network. This, in turn, leads to reduced travel times, reduced fuel consumption, and reduced emissions. For the general public, accurate predictions can help them plan their travel routes, avoid congested roadways, and arrive at their destinations faster. This, in turn, leads to improved quality of life and reduced stress levels.

Time series forecasting methods have emerged as a critical tool in many fields. The ability to predict future trends and patterns from historical data has been critical to many industries, including finance, retail, healthcare, and manufacturing [9], [10]. Time series forecasting techniques are particularly useful when dealing with data that varies over time, such as stock prices, sales, and weather patterns. These methods allow analysts to identify trends, patterns, and cycles in data that can be used to inform decision-making.

The origins of time series forecasting can be traced back to the early 20th century when pioneers in the field, such as Yule and Walker, introduced statistical techniques to analyze data over time. These early methods focused on identifying trends and patterns in data using simple moving averages and exponential smoothing techniques. Over time, more sophisticated methods, such as ARIMA, ARCH, and GARCH, were developed to address the limitations of earlier approaches [6], [11]. These methods allowed analysts to model complex data patterns, including seasonal and cyclic patterns, and to account for the impact of external factors, such as changes in economic policy or weather events. Today, time series forecasting is a mature field with a wide range of applications and a rich set of tools and techniques. One such example is the use of time series model in quantifying the reliability and survivability of cellular networks as mentioned in [12]. Advances in computing power, machine learning, and artificial intelligence have further expanded the range of methods available to analysts [13]. As data becomes more complex and varied, time series forecasting will continue to play an essential role in helping organizations make informed decisions based on historical trends and patterns.

Time series methods

Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) is a popular time series method used in various fields such as finance, economics, and transportation. ARIMA is a statistical model that uses past observations to predict future values. In the context of urban transportation, ARIMA can be used to predict traffic flow and congestion levels. ARIMA takes into account various factors that can influence traffic flow, such as trends, seasonality, and other external factors. The model is widely used because it is simple to understand and easy to implement. It can provide accurate predictions and help urban planners and policymakers make informed decisions [14]–[16].

ARIMA is an acronym for Autoregressive Integrated Moving Average. The autoregressive component of the model takes into account the past values of the variable being predicted. The integrated component of the model accounts for the effects of differencing, which is a technique used to stabilize the variance of the time series data. The moving average component of the model models the errors or residuals of the time series. ARIMA is a versatile model that can handle various types of time series data, including stationary and non-stationary data.

The ARIMA formula can be represented as follows:

$$\phi(B)\nabla^{d} x_{d} = \theta(B)\varepsilon_{t}$$

$$E(\varepsilon_{t}) = 0, Var(\varepsilon_{t}) = \sigma_{t}^{2}, E(\varepsilon_{t}\varepsilon_{S}) = 0, s \neq t$$

$$Ex_{s}\varepsilon_{t}, \forall s < 1$$

The reverse operator is represented by B, while the error term at time t is represented by εt. There are three parameters in the model: p, d, and q. Autoregressive is denoted by p, the degree of non-seasonal difference is denoted by d, and the order of moving average is denoted by q. ARIMA has been used to predict traffic flow and congestion levels in urban networks. The model can take into account various external factors such as weather, events, and construction activities that can influence traffic flow. ARIMA can provide short-term and long-term predictions that can help urban planners and policymakers make informed decisions. Short-term predictions can be used to manage traffic flow in real-time, while long-term predictions can be used to plan infrastructure and transportation projects. ARIMA is a valuable tool that can be used to improve the efficiency and safety of urban transportation systems.

Autoregressive Integrated Moving Average (ARIMA) has several strengths that make it a popular time series method for predicting traffic flow and congestion levels in urban networks. Firstly, ARIMA can capture the linear relationships between past observations and future values of traffic flow and congestion levels. This means that the model can identify patterns and trends in the data that can be used to make accurate predictions. Secondly, ARIMA can handle data with seasonal patterns. This is important for traffic data because traffic patterns can vary based on the time of day, day of the week, and season of the year. Lastly, ARIMA can provide a measure of forecast uncertainty. This allows urban planners and policymakers to assess the accuracy of the predictions and make informed decisions based on the level of uncertainty.

The model may not be able to capture complex nonlinear relationships in the data. This means that the model may not be able to capture the effects of external factors that can influence traffic flow, such as weather, events, and construction activities. Secondly, ARIMA assumes that the data is stationary, which may not be the case for traffic data. Traffic patterns can change over time due to changes in infrastructure, population, and economic activity. Lastly, ARIMA may not perform well when there are sudden changes or disruptions in traffic flow. This is because the model is designed to capture gradual changes in the data and may not be able to adjust quickly to sudden changes.

There are more advanced time series models that can capture complex nonlinear relationships in the data, account for non-stationary data, and handle sudden changes in traffic flow. These models include Autoregressive Conditional Heteroskedasticity (ARCH), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and Vector Autoregression (VAR). These models are more complex than ARIMA and require more data and computational power. However, they can provide more accurate predictions and help urban planners and policymakers make more informed decisions.

Seasonal Autoregressive Integrated Moving Average (SARIMA)

Seasonal Autoregressive Integrated Moving Average (SARIMA) is a time series forecasting method that is widely used in various industries, including transportation, finance, and energy. SARIMA, which builds upon the ARIMA model, has two extra components. These are the seasonal autoregressive (SAR) component and the seasonal moving average (SMA) component. These additional components account for the influence of previous values and past forecast errors across multiple seasonal periods on the current value.

$$\nabla^d \nabla_S^D x_t = \frac{\theta(B)\phi_s(B)}{\phi(B)\phi_s(B)} \varepsilon_t$$

The time series is represented by x_t, while the difference operation is represented by ∇. The reverse shift operator is denoted by B, and the period length is represented by s. The white noise sequence is represented by t. The parameters p, d, and q have the same meaning as in the ARIMA model. The parameters P, D, Q, and s denote seasonal autoregressive, seasonal difference, seasonal moving average order, and the length of the seasonal period, respectively.

SARIMA is a variant of the Autoregressive Integrated Moving Average (ARIMA) model, which incorporates seasonality into the model. This makes SARIMA particularly useful in traffic prediction, where traffic patterns tend to exhibit seasonal patterns, such as rush hour traffic. The SARIMA model helps in predicting future traffic volumes accurately by taking into account both seasonal patterns and any other underlying trends and patterns in the data. SARIMA involves several parameters, including the order of the autoregressive (AR) and moving average (MA) components, as well as the order of differencing required to make the time series stationary. Additionally, SARIMA requires specifying the seasonal periods in the data, which can be challenging in traffic prediction since there may be multiple seasonal periods (e.g., daily and weekly patterns). Despite the complexity of the model, SARIMA can be a powerful tool for traffic prediction, providing accurate forecasts that can help traffic planners make informed decisions about traffic management.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model has several strengths that make it a popular choice for traffic prediction. One of its main strengths is its ability to capture seasonal patterns in traffic flow and congestion levels. By incorporating seasonality into the model, SARIMA can account for daily, weekly, and even yearly patterns in traffic volumes and congestion levels. This makes it a powerful tool for traffic planners, who can use SARIMA forecasts to anticipate traffic patterns and adjust traffic management strategies accordingly.

SARIMA can handle non-stationary data by differencing the time series. Non-stationary data is common in traffic prediction, where traffic volumes and congestion levels may exhibit trends or cyclical patterns over time. By differencing the time series, SARIMA can remove these trends and make the data stationary, which is necessary for accurate forecasting. This makes SARIMA a versatile model that can be applied to a wide range of traffic datasets.

In addition, SARIMA can provide a measure of forecast uncertainty, which is important in traffic prediction where accurate forecasting is critical for traffic management decisions [17]. The model can produce confidence intervals around the forecasts, which provide a measure of how certain the model is about its predictions. This allows traffic planners to assess the reliability of the forecasts and make informed decisions based on the level of uncertainty.

SARIMA has several limitations that should be considered when using it for traffic prediction. One limitation is that it may not be able to capture complex nonlinear relationships in the data. Traffic flow and congestion levels may be influenced by a wide range of factors, including weather conditions, special events, and road closures, among others. SARIMA assumes a linear relationship between these factors and traffic volumes, which may not always be accurate.

SARIMA assumes that the data is stationary after differencing, which may not always be the case for traffic data. Sudden changes or disruptions in traffic flow can make the data non-stationary, which can lead to inaccurate forecasts. Careful consideration must be given to the model parameters and data pre-processing steps to ensure that the data is stationary before applying SARIMA. SARIMA may not perform well when there are sudden changes or disruptions in traffic flow. For example, accidents, road closures, or other unexpected events can cause sudden changes in traffic volumes and congestion levels, which may not be accurately captured by the model. In these cases, other forecasting methods or real-time monitoring systems may be more appropriate for predicting and managing traffic flow.

Vector Autoregression (VAR)

Vector autoregression (VAR) is a statistical method used to model the interdependence between multiple time series variables. VAR models are commonly used in the analysis of macroeconomic time series data, but they can also be applied to other fields such as traffic prediction. In the context of traffic prediction, VAR models can be used to model the interactions between different road segments or intersections in the urban network. This allows for a more accurate prediction of traffic flow and congestion levels, which can help in the planning and optimization of traffic management systems. We provide a basic univariate AR(p) model that excludes any potential exogenous variables and may be stated as:

$$y_t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \varepsilon_t$$

where y_t is impacted by the p previous values, a constant (μ), and a random noise (ε_t).
The vector of n simultaneously endogenous factors is denoted by:

$$y_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{n,t} \end{bmatrix}$$

The vector with n elements can be expressed as a function of n constants, previous p values of Yt, and a vector of n random disturbances ϵt that are present at each time step:

$$y_t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \epsilon_t$$

Where, the matrix of the coefficients are as follows:

$$\Phi_1 = \begin{bmatrix} \phi_{i,11} & \phi_{i,12} & \cdots & \phi_{i,1n} \\ \phi_{i,21} & \phi_{i,22} & \cdots & \phi_{i,2n} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{i,n1} & \phi_{i,n2} & \cdots & \phi_{i,nn} \end{bmatrix}$$

And and ϵt as:

$$\epsilon_t = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{bmatrix}$$

With the conditions that Eϵt = 0 and, $E\epsilon_t\epsilon_s' = \{ \begin{matrix} \Sigma, & t = s \\ 0, & t \neq s \end{matrix}$

VAR models can capture the dynamic relationships between variables over time. This means that VAR models can be used to analyze the impact of one variable on another, as well as the feedback loops between different variables. In the case of traffic prediction, VAR models can be used to model the impact of traffic volume on congestion levels, as well as the impact of congestion levels on travel time and traffic volume. By modeling these complex interactions, VAR models can provide a more accurate and comprehensive picture of traffic patterns in the urban network. VAR models can be used to model any number of variables, and they can be easily modified and updated as new data becomes available. This makes VAR models well-suited to the dynamic and constantly evolving nature of traffic patterns in the urban network.

VAR models can be used to capture the interdependencies between different road segments or intersections in the urban network. This allows transportation planners and traffic management systems to gain a more comprehensive understanding of the complex relationships between different variables and make more informed decisions about traffic management strategies. By modeling the interactions between different road segments and intersections, VAR models can also help to identify potential bottlenecks and other sources of congestion, which can be targeted for improvement. VAR models can handle multiple time series data. This is particularly important in the context of traffic prediction, where there may be many different variables that influence traffic flow and congestion levels. VAR models can be used to model the impact of these variables on each other, as well as their collective impact on traffic patterns in the urban network. This can help transportation planners and traffic management systems to identify the most effective strategies for improving traffic flow and reducing congestion.

VAR models can also provide a measure of forecast uncertainty, which is another key strength of this approach. By estimating the degree of uncertainty associated with each forecast, transportation planners and traffic management systems can make more informed decisions about the allocation of resources and the implementation of traffic management strategies. This can help to reduce the likelihood of unexpected traffic disruptions and improve overall traffic flow in the city. The models may not be able to capture complex nonlinear relationships in the data. This is because VAR models assume that the relationships between variables are linear, which may not always be the case for traffic data. As a result, VAR models may not be able to fully capture the complex dynamics of traffic flow and congestion in the urban network.

These models may require a large amount of data to accurately estimate the model parameters. This can be particularly challenging in the context of traffic prediction, where data may be sparse or difficult to collect. Additionally, the accuracy of VAR models may be sensitive to the choice of model parameters and the specification of the model structure. Therefore, it is important to carefully evaluate the assumptions and limitations of VAR models when using this approach for traffic prediction.

Exponential Smoothing (ETS)

Exponential smoothing (ETS) is a widely used time series forecasting technique that is based on the principle of weighted averages of past observations. This method is particularly useful for predicting future values of a time series that exhibit patterns such as trends, seasonality, and other systematic variations. The ETS method applies a smoothing factor to the historical data to create a smoothed forecast. The smoothing factor is usually chosen to give more weight to the more recent observations, and less weight to the older ones.

Simple exponential smoothing has the following component form:

$$\begin{aligned} &\text{Forecast equation} && \hat{y}_{t+h|t} = \ell_t \\ &\text{Smoothing equation} && \ell_t = \alpha y_t + (1-\alpha)\ell_{t-1}, \end{aligned}$$

where l t represents the series' level (or smoothed value) at time t. Setting h = 1 yields the fitted values, while setting t = T yields the genuine predictions beyond the training data.
The forecast equation demonstrates that the predicted value at time t + 1 is the estimated level at time t. The level smoothing equation (also known as the level equation) offers the estimated level of the series at each period t.
Holt expanded simple exponential smoothing to make it possible for trend predictions in data. A prediction equation and two smoothing equations are used in this method:

$$\begin{aligned} &\text{Forecast equation} && \hat{y}_{t+h|t} = \ell_t + hb_t \\ &\text{Level equation} && \ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\ &\text{Trend equation} && b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}, \end{aligned}$$

where l_t denotes an estimate of the series' level at time t, b_t denotes an estimate of the series' trend (slope) at time t, $0 \le \alpha^* \ge 1$ is the smoothing parameter for the level, and $0 \le \beta^* \ge 1$ is the smoothing parameter for the trend.

The method is able to capture trend, seasonality, and other variations that can occur in the data. For example, when a time series exhibits a clear trend, ETS can be used to predict future values by adjusting the weights given to past observations to reflect the trend. Similarly, when a time series exhibits seasonal patterns, ETS can be used to predict future values by adjusting the weights given to past observations to reflect the seasonal variations.

By adjusting the weights given to past observations, ETS can effectively model these patterns, which can be particularly useful for predicting traffic patterns over time. Additionally, ETS can provide a measure of forecast uncertainty, which can help transportation planners and engineers make more informed decisions about infrastructure planning and management. Another strength of ETS is its ability to handle missing data. This is particularly useful for traffic data, which may have gaps due to sensor malfunctions, construction, or other factors.

However, there are also limitations to using ETS for traffic forecasting. One limitation is that it may not be able to capture complex nonlinear relationships in the data. For example, if there are interactions between traffic patterns and weather conditions, ETS may not be able to model these relationships effectively. Additionally, ETS assumes that the data is stationary, which may not always be the case for traffic data. Traffic flow can be affected by a variety of factors, such as construction, accidents, or changes in road conditions, which can make the data non-stationary. Finally, ETS may not perform well when there are sudden changes or disruptions in traffic flow, such as a major accident or a road closure. In these situations, other forecasting techniques, such as autoregressive integrated moving average (ARIMA) or machine learning algorithms, may be more effective.

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that has gained popularity in recent years, especially in the field of time series prediction. Unlike traditional neural networks, LSTM has a unique architecture that allows it to store and process information over time [18]–[20]. This makes it particularly suitable for analyzing sequences of data, such as those found in stock prices, weather patterns, or even the movements of pedestrians in a busy city. LSTM is known for its ability to learn complex patterns in the data, such as trends, seasonal variations, and sudden changes in behavior. This makes it a powerful tool for predicting future trends and making accurate forecasts. LSTM has been successfully used in a wide range of applications, including speech recognition, natural language processing, and image recognition.

The LSTM calculation process can be described as follows:

The first step involves calculating the forget gate (ft), which determines how much information is discarded. The calculation for ft can be expressed as follows:

$$\mathrm{f}_t = \sigma\left(U_f x_t + W_f h_{t-1} + b_f\right)$$

The equation for ft involves adjustable parameter matrices or vectors, denoted as Uf, Wf, and bf, which represent the forgetting gate and can be optimized during neural network training. The sigmoid activation function, represented as σ, is applied to the weighted sum of the input and previous cell state.

The second step involves calculating the input gate (it), which determines the amount of information used to update the cell state.

$$\mathrm{i}_t = \sigma\left(U_i x_t + W_i h_{t-1} + b_i\right)$$

The calculation for it also involves adjustable parameter matrices or vectors, denoted as Ui, Wi, and bi, which represent the input gate and can be optimized during neural network training. The formula for the newly acquired information C˜t can be expressed as follows:

$$\tilde{C}_t = \tan h\left(U_{\tilde{C}} x_t + W_{\tilde{C}} h_{t-1} + b_{\tilde{C}}\right)$$

The equation for the newly acquired information, denoted as C˜t, also involves adjustable parameter matrices or vectors, represented as UC˜, WC˜, and bC˜, which can be optimized during neural network training. The hyperbolic tangent activation function, represented as tanh, is applied to the weighted sum of the input and previous cell state.

The third step involves updating the cell state, which is calculated as follows:

$$\mathrm{C}_t = \mathrm{f}_t * \mathrm{C}_{t-1} + \mathrm{i}_t * \tilde{C}_t$$

The equation involves a matrix multiplication operation represented by the symbol ∗. The cell state, denoted as Ct, is updated based on the results of the forget gate and the newly acquired information. Since the cell state interacts linearly with other LSTM units, information can be retained for a longer period of time.

The fourth step involves calculating the output gate (ot), which generates the hidden layer state variable ht at time t. The formulas for calculating ot can be expressed as follows:

$$\mathrm{o}_t = \sigma\left(U_o x_t + W_o h_{t-1} + b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

The equation for calculating the output gate (ot) also involves adjustable parameter matrices or vectors, denoted as Uo, Wo, and bo, which represent the output gate and can be optimized during neural network training.

The fifth and final step involves calculating the output (yt) using the following formula:

$$\mathrm{y}_t = W_d h_t + b_d$$

The equation for calculating the output (yt) involves adjustable parameter matrices or vectors, represented as Wd and bd, which belong to the output layer and can be optimized during neural network training.

One area where LSTM has shown particular promise is in predicting traffic flow and congestion levels in urban networks. Traffic prediction is a complex problem that depends on a variety of factors, including the time of day, weather conditions, and the behavior of individual drivers. Traditional traffic models rely on statistical methods and assumptions about traffic patterns, which can be imprecise and fail to capture the complex interactions between different elements of the traffic system. LSTM, on the other hand, is capable of learning the patterns and relationships within the data itself, making it a more accurate and flexible tool for traffic prediction. By analyzing historical traffic data and other relevant factors, LSTM can make accurate predictions about traffic flow and congestion levels, which can help city planners and transportation authorities optimize traffic flow and reduce congestion.

One of the most significant strengths of LSTM is its ability to capture complex nonlinear relationships in the data. This means that the model can learn to identify patterns and relationships that are difficult to detect using traditional statistical methods. Additionally, LSTM can handle multiple input variables and time lags, making it more versatile than many other prediction models. This allows it to analyze complex data sets with many different factors, such as weather patterns, traffic flow, and financial data. Another important strength of LSTM is its ability to learn from past errors to improve future predictions. This is because LSTM has a built-in feedback mechanism that allows it to adjust its predictions based on past performance. This makes it more accurate and reliable over time, improving its usefulness in many different applications.

LSTM requires a large amount of data to train the model effectively. This means that the accuracy of the predictions is directly tied to the amount of data available, which can limit its usefulness in some applications. Additionally, LSTM can be computationally expensive to train and implement, especially for large data sets. This can make it difficult for smaller organizations or individuals to utilize the model effectively. LSTM can be difficult to interpret and diagnose if the model does not perform well. This is because the model is based on complex mathematical algorithms, and errors can be difficult to identify and correct without extensive knowledge of the model and its underlying principles [21].

Conclusion

When considering the selection of a time series method for predicting traffic flow and congestion, it is crucial to take into account the unique characteristics of the data and the objectives of the prediction task. Among the popular time series methods for traffic prediction are ARIMA, SARIMA, VAR, ETS, and LSTM.

ARIMA and SARIMA are suitable for capturing linear and seasonal relationships between past observations and future traffic flow and congestion levels. ARIMA is a robust method that can handle data with seasonal patterns and provide a measure of forecast uncertainty. However, it may not be suitable for capturing complex nonlinear relationships in the data, and it assumes that the data is stationary, which may not always be the case for traffic data. Moreover, sudden changes or disruptions in traffic flow may affect the performance of ARIMA.

SARIMA, on the other hand, is for capturing seasonal patterns in traffic flow and congestion levels. It can handle non-stationary data by differencing the time series and can provide a measure of forecast uncertainty. However, it may not be able to capture complex nonlinear relationships in the data, and it assumes that the data is stationary after differencing, which may not always be the case for traffic data. Additionally, sudden changes or disruptions in traffic flow may also affect the performance of SARIMA.

VAR is an appropriate method for modeling interdependencies between different road segments or intersections in an urban network. It can handle multiple time series data and provide a measure of forecast uncertainty. However, it may not be able to capture complex nonlinear relationships in the data, and it assumes that the relationships between the variables are linear, which may not always be the case for traffic data. Moreover, a significant amount of data may be required to accurately estimate the model parameters for VAR.

ETS can capture trends, seasonality, and handle missing data in traffic flow and congestion levels. It can provide a measure of forecast uncertainty. However, it may not be able to capture complex nonlinear relationships in the data, and it assumes that the data is stationary, which may not always be the case for traffic data. Furthermore, sudden changes or disruptions in traffic flow may affect the performance of ETS. LSTM can capture complex nonlinear relationships in the data. It can handle multiple input variables and time lags and learn from past errors to improve future predictions. However, LSTM requires a large amount of data to train the model and can be computationally expensive to train and implement. Additionally, the model can be difficult to interpret and diagnose if it does not perform well.

One limitation of the study is that it focuses on the technical aspects of time series methods, such as their ability to capture complex patterns and handle non-stationary data. However, it does not consider the practical limitations of implementing these methods in real-world settings. For example, the study does not address the data collection and processing requirements of each method or the feasibility of using them in different transportation contexts, such as rural areas or developing countries. Therefore, the applicability and scalability of the methods need to be considered in future research, along with their technical performance.

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