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Urban Arterial Mid-Block Traffic Forecasting: Case Study of Kathmandu Ring Road

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Abstract:
Lack of proper transportation management system creates numerous traffic problems such as traffic congestion and accidents. Traffic management, especially in urban areas, requires the application of intelligent transportation systems (ITS) to counter these problems. Predicting short-term traffic flow using different time series forecasting models is an essential aspect of ITS. The frequently used forecasting models such as ARIMA, SARIMA, etc., require an extensive collection of traffic data, which may not be feasible for predicting the short-term traffic volume. On the other hand, the multiplicative decomposition forecasting model offers a viable solution to the problem as it requires a minimal set of data. In this study, the efficacy of the multiplicative decomposition forecasting method in two sections of the Kathmandu ring road has been validated. The three consecutive day traffic data was collected through videographic survey during the rush hours. The first two days' data were used to predict the third-day data, which was validated with the observed field data. The Mean Absolute Percentage Error (MAPE) was found to be 10.55% and 10.59% for the study sections, which were between the permissible limit of 9% to 16% required for ITS applications. The results look promising and might become a valuable tool for short-term traffic condition forecasting in ITS.
Keywords: *ITS application, Short-term traffic forecasting, Multiplicative decomposition model*

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INTRODUCTION

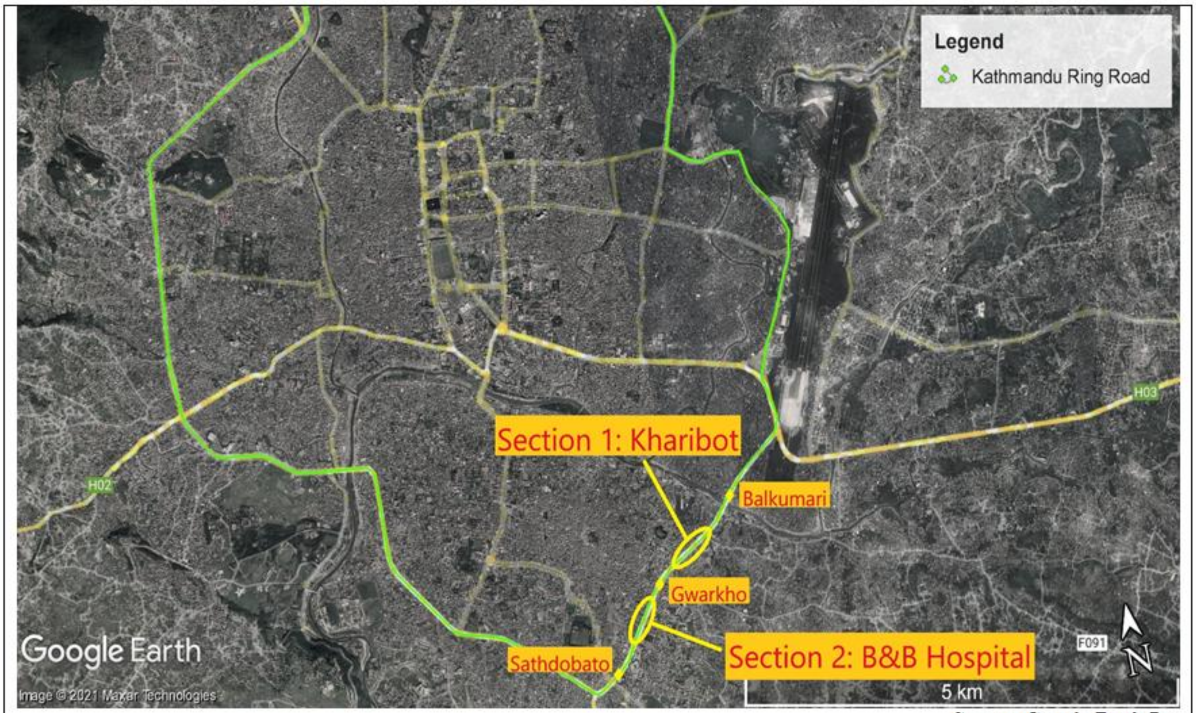
Road transportation is one of the indispensable infrastructures of a country for its economic prosperity. A sustainable transportation system is a primary requirement for the smooth functioning of traffic. Traffic volume, being a dynamic factor, greatly influences in design and operation of the transportation system. The failure to address this factor in the analysis can cause severe traffic operational problems, especially in urban roads: congestion and accidents. These problems can be solved by implementing a properly analyzed and designed traffic management system that encompasses the dynamic behavior of the traffic flow. Intelligent transportation system incorporates the dynamic nature of traffic flow based on information, communication, and satellite technologies to alleviate traffic congestion and accident[1]. The requirement of the system is even more inevitable in important urban areas like Kathmandu, Nepal.

The Kathmandu city- the capital of Nepal- is heavily populated due to which it bears dynamic traffic characteristics. Vehicles of different categories are observed in various links of the road network of the valley. One of the heavily used arterial road is the Kathmandu ring road. The lack of assessment of this mixed traffic volume in the ring-road has resulted in various problems like traffic delay and congestion. Implementation of an Intelligent Transportation System with a suitable short term forecasting method might be useful in managing traffic[2]. This study is intended to examine the validity of the Multiplicative Decomposition method for forecasting short-term traffic data, which could be used in the future development of ITS.

The volume of traffic expected on the road in the next few minutes to an hour is an essential research problem in intelligent transportation system applications[3]. This problem can be addressed through different mathematical computational techniques: time series analysis[4], regression[5], and Kalman Filtering method[6]. The time series forecasting method primarily employs the ARIMA model to predict the huge traffic volume[7]. However, because of the requirement of excessive traffic data values and its intricate model coefficient, the ARIMA model might not always be compatible with forecasting the short-term traffic data[8]. Multiplicative decomposition time series analysis can be an effective alternative for overcoming the shortcomings posed by the ARIMA model. This classical technique is easily executable, with its simple methodology that can be performed in Excel sheets, Python, and MATLAB programs. The method has been executed with incredible success in research of various fields such as wind speed[9], railway passenger growth[10], and tissue growth[11].

Case Study:

For developing a forecasting model using the multiplicative decomposition method, two busy mid-block sections of the southern ring-road of the Kathmandu Valley were selected. The mid-block sections of Kharibot (Section 1) and B&B hospital (Section 2) were both of 8 lanes, each lane having a standard width of 3.5m as measured from the field. We used videographic method to collect traffic volume data during rush hours (9-11 am and 4-6 pm) for three consecutive days of August 2021. The vehicular characteristics of the sections were attributed to the heterogeneous flow of vehicles.



Source: Google Earth Pro

Figure 1: Location Map of Studied Mid-block Sections

Figure 2: Kharibot (Section 1)

Figure 3: B&B Hospital (Section 2)

LITERATURE REVIEW

Kornkamal Laung-Iem et al. (2021), in their research paper, demonstrated the implication of the multiplicative decomposition model in forecasting prices of biodiesel from 2017 to 2036. The past biodiesel prices over the period of 120 months were accumulated from the energy policy and planning office, Ministry of Energy of Thailand. The collected data was then plotted to obtain the existing trend of the biodiesel prices with respect to time. The multiplicative decomposition method was then used to decompose the collected time-series data into its components: trend, seasonality, and residue. The forecasting model showed a progressive decreasing trend of the prices of biodiesel from 2017 to 2036. Furthermore, the model also showed 0.24651 MAPE (mean absolute present error), indicating the efficacy of the multiplicative decomposition model in predicting the future trend[12].

G. Omkar & S. Vasantha Kumar (2017) conducted a study to forecast the traffic flow in an urban mid-block section using the time series decomposition model. As the Autoregressive integrated moving average (ARIMA) model required a large number of data to predict traffic volume correctly, another time series method such as the multiplicative decomposition model was more found to be more feasible in this case. A mid-block road section in Tamilnadu was selected to collect the traffic volume data of two consecutive days between 7-11 am. The proposed model was used, and the mean absolute percentage error (MAPE) was observed to fall in the acceptable range of 9-16 for the predicted traffic volume data[13].

The forecasting model using the time series decomposition method was performed on historical railway passengers' data by Vineeta Prakaulya et al. (2017). This model was utilized to interpret various time series components such as seasonality, trend, cyclic, random, and each component separately. The obtained negligible autocorrelation, which was estimated using the Durbin Watson test, indicated the suitability of this model for forecasting[10].

In the study conducted by S. Vasantha Kumar & Lelitha Vanajakshi (2015), they seek to overcome the problem of the need for a large volume of data while using the ARIMA model by presenting a seasonal ARIMA (SARIMA) model. This model could be used where less amount of data is available. A roadway section in India was selected for the traffic flow study, and the SARIMA model was developed. This model was used to forecast the data, which was later validated with the actual ones. Finally, mean absolute percentage error(MAPE) was obtained, which fell into an acceptable range[8].

In 2015, V. Prema and K. Uma Rao conducted a short-term prediction of wind speed using various time series models. Multiple models were used to forecast a day ahead data, and those predicted data were compared with real ones. Finally, a multiplicative decomposition model was developed and tested for various samples and weather conditions. The final Result produced the least error, which validated the effectiveness of the model[9].

In their research paper, Jianguang Deng et al. (2010) used time-series analysis to forecast Singapore's short-term electricity demand. The time series models- seasonal Arima Model and multiplicative decomposition- were used for predicting the electricity demand. The errors accumulated during the forecast were compared between both methods. The forecasted results showed that both techniques were successful in predicting the short-term electricity demand in Singapore. Furthermore, the efficiency in generating accurate forecasts was found to be greater for the multiplicative decomposition method than the ARIMA model[14].

Using a reliable method of forecasting, H.K. Temraz et al. (1996) predicted electric load. Before developing the actual forecasting model, a suitable model for fitting the data was chosen. Then following the sequential process of identification, estimation, and checking, the model was created. The additive and multiplicative decomposition methods were then used with the model for predicting the electric load. The suitability of the decomposition model was then tested by forecasting the monthly peak load of a massive network of electric power. The obtained results were then evaluated and compared to verify the credibility of using the decomposition technique. It was found that the method yielded accountable results with reasonable accuracy[15].

Although several studies have been carried out to forecast long-term traffic conditions using different forecasting models, few investigations have been conducted to project the short-term traffic data. The mixed traffic conditions observed in our case study have not yet been incorporated by the past studies. Furthermore, researches regarding short-term traffic prediction are absent in the context of Nepal. This study addresses the above-mentioned issue by implementing the multiplicative decomposition model in a specific road section of Kathmandu Valley.

METHODOLOGY

The methodology for the study of the ring road mid-block section followed a series of steps extracted from the range of previous literature. The concept of vehicle classification for the data collection was based on the Indo-Highway Capacity Manual. The traffic data was collected at the mid-block section of Kharibot and BNB hospital through a video graphic survey conforming to the manual. The data was recorded at the rush hours (9:00 to 11:00 hours and 16:00 to 18:00 hours) from Tuesday to Thursday in August 2021. It was manually counted into six different categories as per the capacity manual. The classified vehicles of different maneuverability and speed attributes were standardized into passenger car units (PCU), which is a common unit in transportation studies. In order to simulate real heterogeneous traffic flow, Stream Equivalency Factor was implemented over the dynamic PCU method. Hence, the traffic volume of each vehicle was converted into the PCU using the stream equivalency equation[16].

Then, the obtained PCU values were used as the input data against time to obtain the existing traffic time-series plot, which was decomposed into its components- trend, seasonality, and residue- by the multiplicative decomposition method. The detailed processes of the Multiplicative Decomposition method include the following steps and are also illustrated by the flowchart:

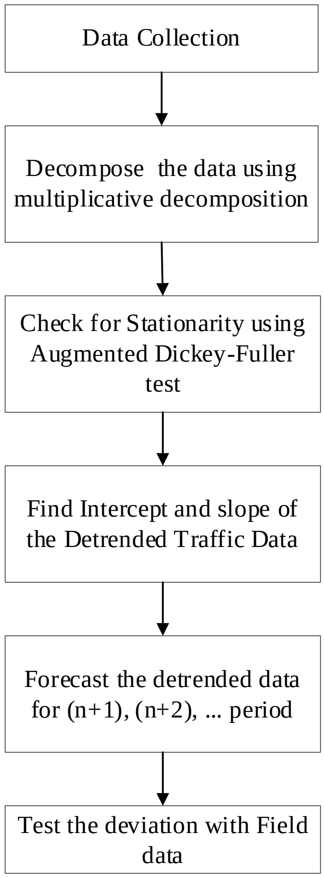


Figure 1: Flowchart illustrating the steps followed in developing multiplicative decomposition model

1. Firstly, the simple moving average of the data was formulated using the given equation.

$$\mathrm{MA}(k) = \frac{1}{k}\sum_{t=1}^{k} Y_t \qquad Eq.(1)$$

   Where,
   K= 2 is the order of the MA process
   Y_t = Value of time series at period t in PCU per hour.

2. Since K=2 is even, Centered Moving Average (CMA) was calculated by taking the average of two moving averages. The CMA was used to derive smooth data free from any seasonal effects.
3. The degree of seasonality, i.e., seasonal factor (SF), was calculated by the following equation.

$$\mathrm{SF}_t = \frac{Y_t}{\mathrm{CMA}} \qquad Eq.(2)$$

4. Averaging the seasonal factors of the same time period will remove irregular seasonal components (e_t) and provide seasonal index (S_t).
5. Trend cycle component requires deseasonalized data (d), which is obtained by the given equation.

$$d = \frac{Y_t}{S_t} \qquad Eq.(3)$$

Then the stationarity of the deseasonalized/detrended data was checked using the Augmented Dickey-Fuller test[17]. Finally, the obtained deseasonalized data were used to forecast the next-day traffic using the given equation.

$$Y_t = T_t \times S_t \times e_t \qquad Eq.(4)$$

The Mean Absolute Percentage Error (MAPE) was employed to validate the predicted data against the observed field data by the following formula.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\mathrm{Flow}_{pred} - \mathrm{Flow}_{obs}}{\mathrm{Flow}_{obs}}\right| \times 100 \qquad Eq.(5)$$

Where n=16 is the number of predicted flows

DATA ANALYSIS AND RESULT

Comparison of the AADT of the classified vehicles in different years

The AADT of the classified vehicle was extracted from the Department of Roads, Nepal(DOR), HMIS unit, Statistics of Strategic Road Network(SSRN) for the preliminary observation of the vehicular flow of the study section. The comparison of the data showed that private vehicles have been more preferred than public ones. The private vehicles such as cars, two-wheelers, etc., have increased drastically, whereas the usage of the public bus has been found to be decreased in the most recent year. The changing trend of the vehicles, as indicated by the bar diagram, shows the heterogeneous flow of the vehicles.

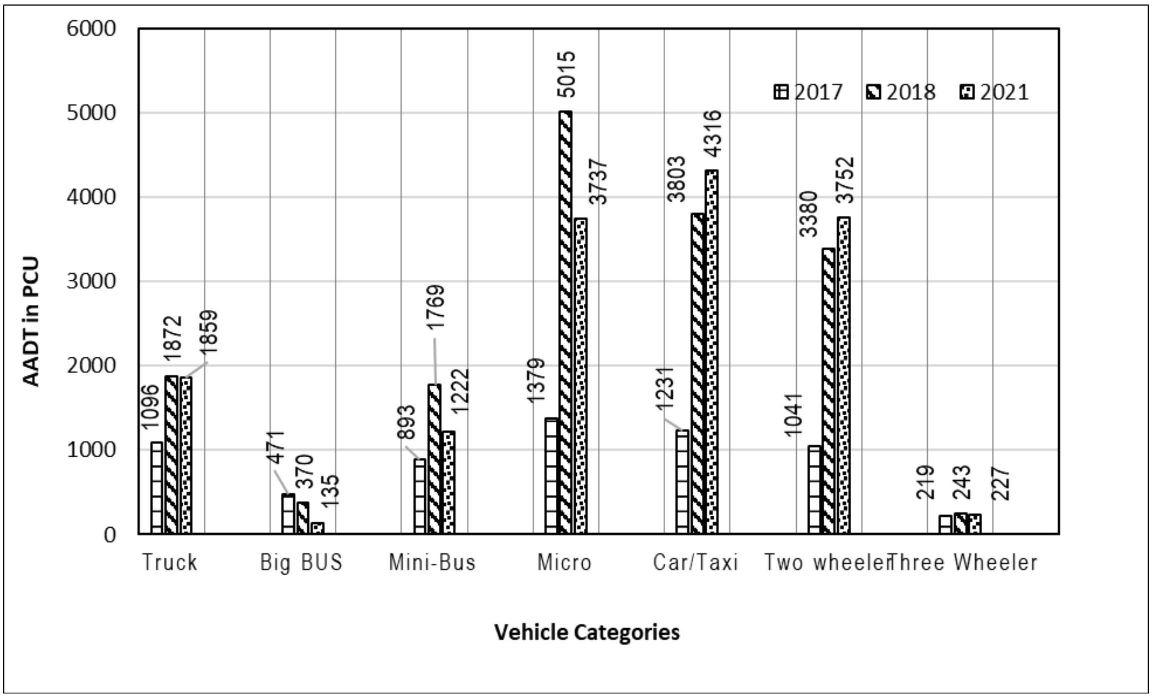


Figure 2: Comparison of AADT at Section 1

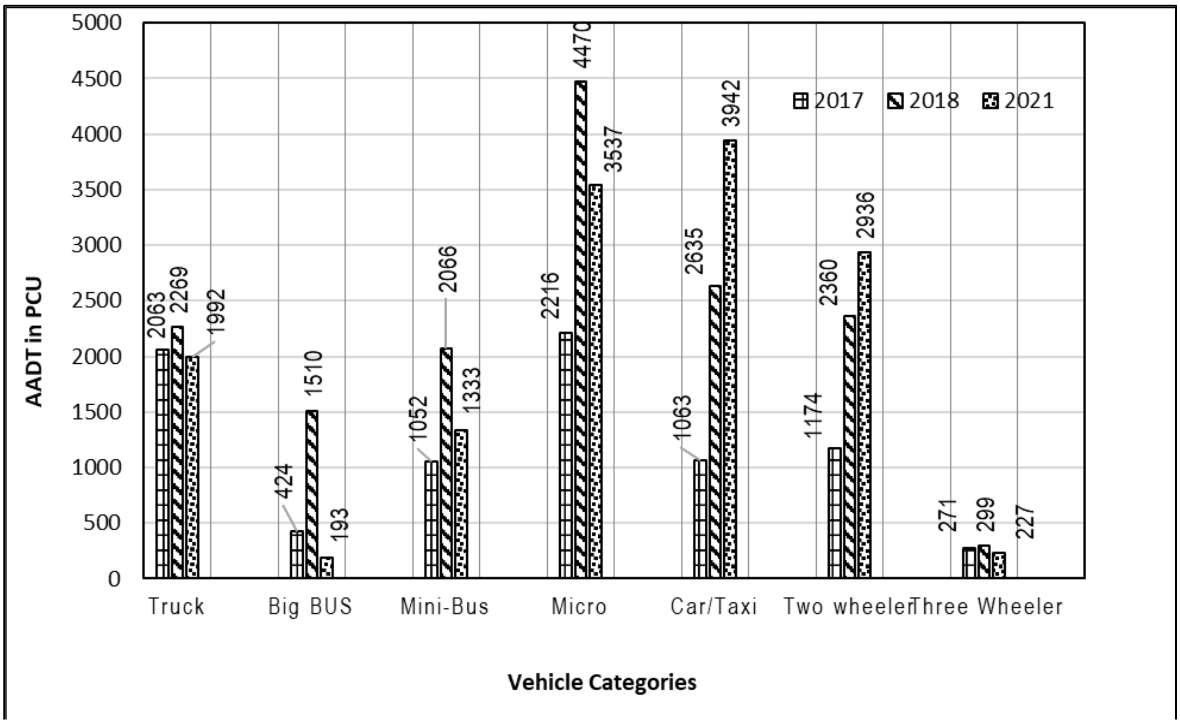


Figure 3: Comparison of AADT at Section 2

Time-series trend of traffic flow in mid-block sections

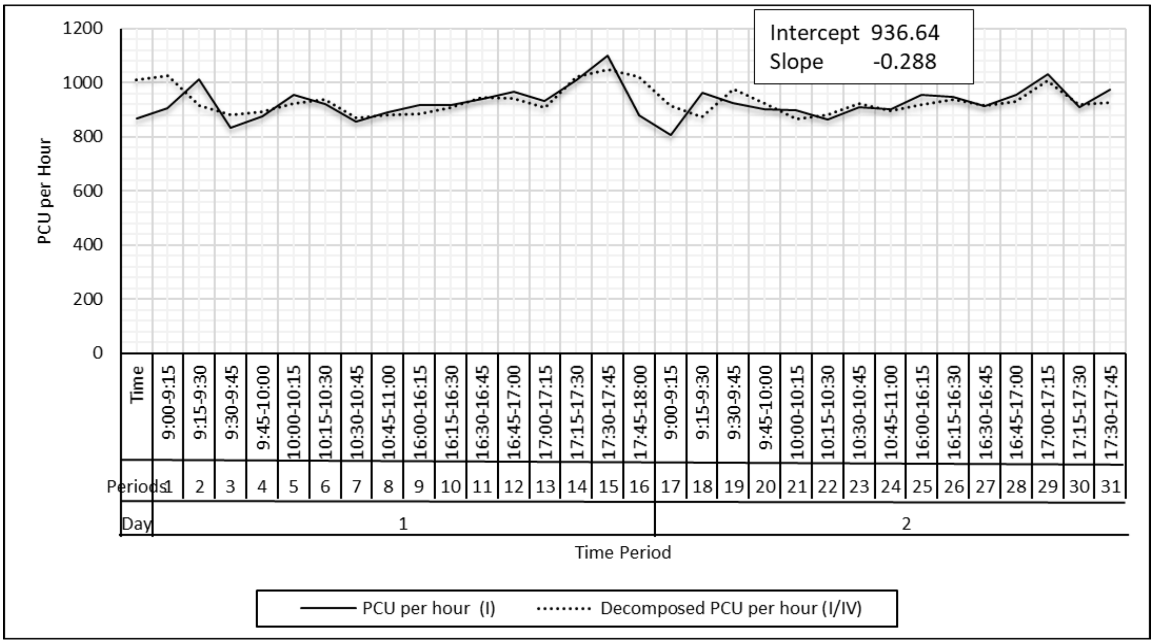


Figure 4: Trend line of Section 1

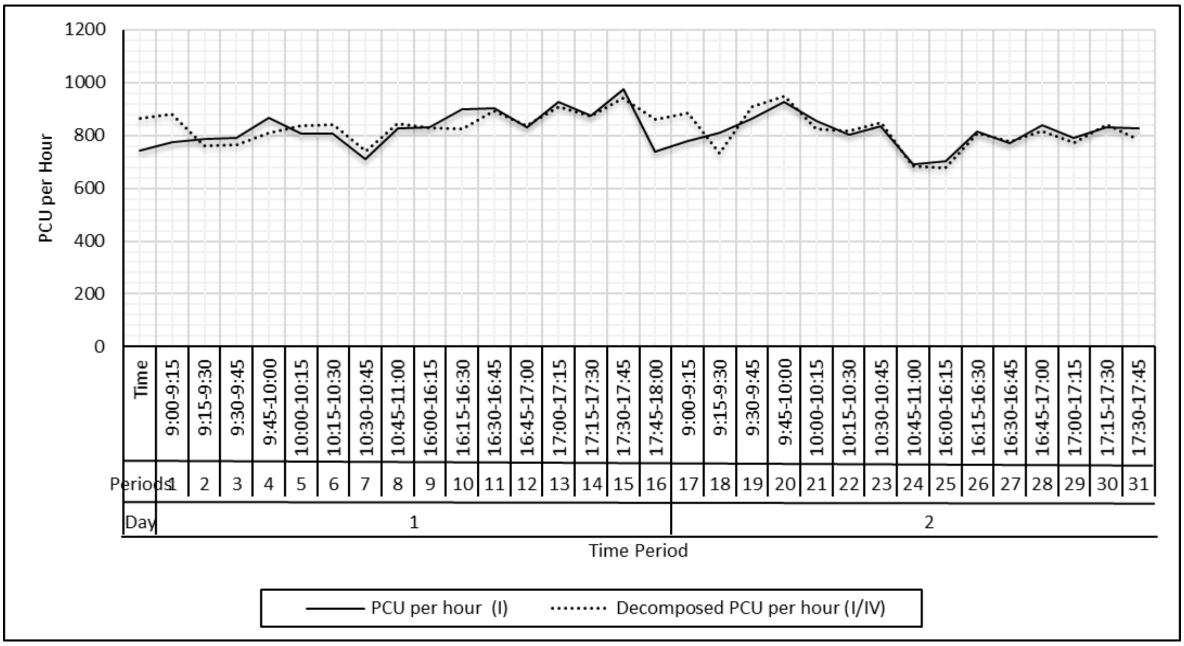


Figure 5: Trend line of Section 2

The time-series trend of both the obtained PCU traffic data and decomposed data taken in both mid-block sections for the two consecutive days is obtained. The slope and intercept of the decomposed trend line are shown in the above figure, which is eventually used to forecast the next-day traffic data.

Checking the stationarity of the decomposed data using the ADF test

The Augmented Dickey-Fuller test, a statistical unit root test, is usually used to check the stationarity of the decomposed time-series data. The two hypotheses are passed in this test, namely the null hypothesis (H0) and the alternative hypothesis (H1). Based on the p-value obtained from the test, the unit root is confirmed in the decomposed time-series data, which is then used to determine the stationarity of the data.

IF p-value > 0.05, H_0 is accepted, which infers the presence of unit root in the time-series data, and indicates the time series is stationary.

IF p-value ≤ 0.05, H_0 is rejected, which infers the presence of unit root in the time-series data and indicates the time series is stationary.

In our case, the python program is written for the decomposed time-series data using the stats model package.

Table 1: Augmented Dickey-Fuller test for section 1

Augmented Dickey-Fuller test Statistic		**t-statistic**	**Probability**
		-3.87814	0.005
Test critical value level:	Level 1%	-3.661	
	Level 2%	-2.961	
	Level 3%	-2.619	

Table 2: Augmented Dickey-Fuller test for section 2

Augmented Dickey-Fuller test Statistic		**t-statistic**	**Probability**
		-4.086635	0.001019
Test critical value level:	Level 1%	-3.661	
	Level 2%	-2.961	
	Level 3%	-2.619	

The ADT test done on both the mid-block sections showed that the decomposed time-series data were stationary. The stationary time-series data were then used for the forecast using the multiplicative decomposition forecasting model.

The traffic data of the Kharibot mid-block (section 1) collected on 3rd and 4th August is used to predict the traffic data for the following day. The predicted data is then compared and validated with the real traffic data taken on the 5th of August using the Mean Absolute Percentage Error. The same process was followed for the B&B mid-block (section 2) for predicting the data taken on the 10th and 11th of August.

Table 3: MAPE calculation table

Day-3	Periods	Time	Forecasted Decomposed PCU		Field Observed PCU		MAPE	
			Section 1	Section 2	Section 1	Section 2	Section 1	Section 2
Morning	1	9:00-9:15	936	848	891	785	10.56	10.59
	2	9:15-9:30	936	846	908	817		
	3	9:30-9:45	936	845	1134	959		
	4	9:45-10:00	935	844	974	957		
	5	10:00-10:15	935	842	1010	997		
	6	10:15-10:30	935	841	1082	905		
	7	10:30-10:45	935	840	1056	906		
	8	10:45-11:00	934	838	1060	930		
Evening	9	16:00-16:15	934	837	1070	937		
	10	16:15-16:30	934	835	1094	945		
	11	16:30-16:45	933	834	1061	1023		
	12	16:45-17:00	933	833	1042	943		
	13	17:00-17:15	933	831	1067	923		
	14	17:15-17:30	933	830	1056	935		
	15	17:30-17:45	932	829	1011	909		
	16	17:45-18:00	932	827	1074	941		
Total			14947	13401	16590	14812		

The MAPE of 10.55% and 10.59% were obtained for the Section 1 and Section 2, respectively. The MAPE for both sections was found within a limit of 9% to 16%, which is acceptable for most Intelligent Transportation Systems.

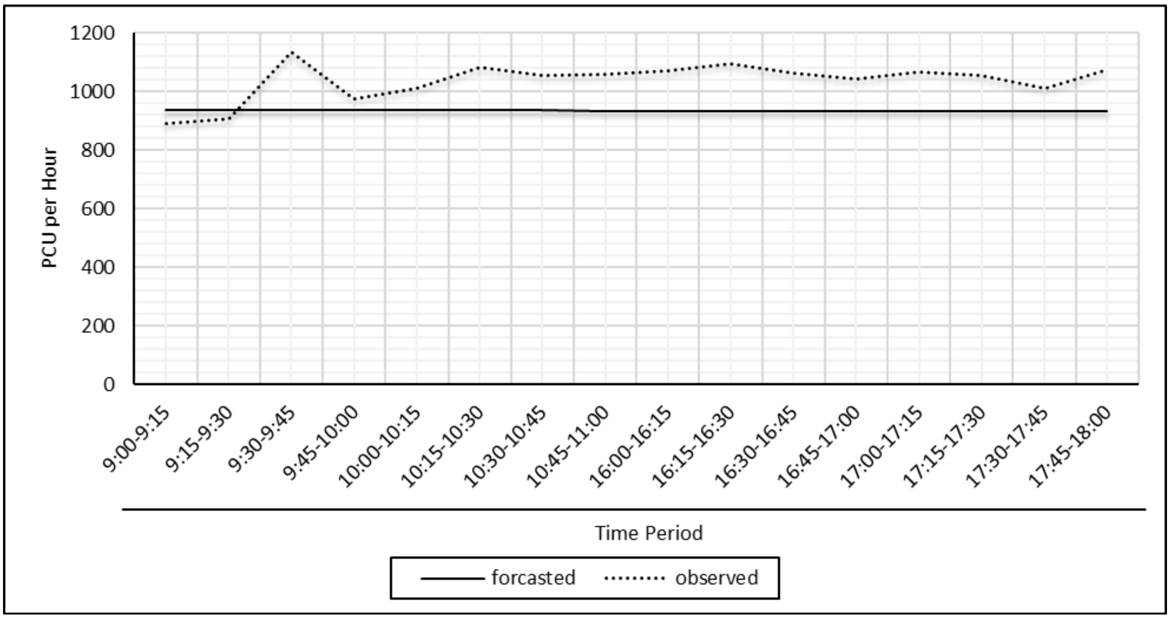


Figure 6: Forecasted and observed traffic data of Section 1

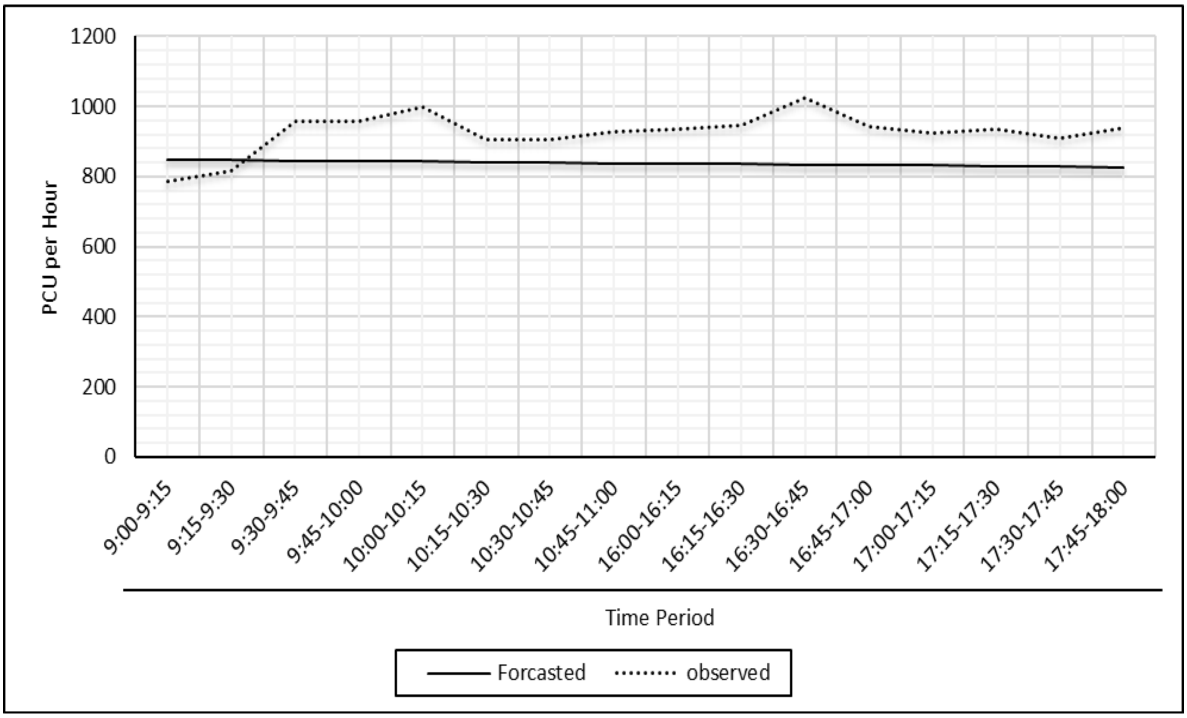


Figure 7: Forecasted and observed traffic data of Section 2

CONCLUSION

Successful prediction of the short-term transportation volume is an indispensable requirement of the ITS. Various forecasting models are used for fulfilling the condition. The primarily used ARIMA model requires substantial data and complicated steps of implementation, which may not always be favorable for forecasting the short-term traffic data as per the requirement of ITS. The multiplicative decomposition forecasting method might be used as an alternative forecasting technique to offset the limitations posed by the ARIMA model. The findings of the current study prove the model's credibility in predicting the short-term traffic trend. This model can be used in the ITS system for forecasting short-term traffic regardless of the heterogeneity of the vehicles.

Our study only incorporates the rush hour period in the morning and evening for forecasting the short-term traffic. However, the peak hour of the entire day could have been used to obtain the comprehensive field data at the desired sections.

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