STATISTICAL MODELLING FOR TEMPORAL VARIATION OF TRAFFIC ON JAMUNA BRIDGE BY VEHICLE CATEGORY USING TIME SERIES DATA

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ABSTRACT

This study examines the temporal variation of traffic on the Jamuna Multipurpose Bridge, one of Bangladesh's most critical transportation corridors, by analyzing three distinct vehicle categories: motorcycles, light vehicles, and large buses. Despite the bridge's strategic importance and continuous toll operation since 1998, limited research has explored how traffic patterns evolve in response to economic conditions, policy changes, and external shocks.

To address this gap, statistical modelling techniques — specifically, autoregressive time series models — were applied to examine both the short-term and long-term influences of economic, religious, and weather events on traffic demand, using 25 years of time series data. The models incorporate economic indicators and event-based indicator variables to estimate the elasticity of traffic volumes with respect to GDP, inflation, consumer price index, and other macroeconomic drivers.

The consumer price index (CPI) emerged as a strong predictor of traffic growth on the Jamuna Bridge, for all three vehicle categories, suggesting that inflationary pressures may shift travel behavior toward affordable or essential modes. Surprisingly, toll increases were often associated with higher traffic volumes, indicating relatively low price sensitivity for passenger vehicles. External disruptions, such as the COVID-19 pandemic, had contrasting effects as motorcycle traffic surged during lockdowns due to the need for personal mobility, while significant bus traffic declined sharply. Seasonal events, such as Eid festivals, and natural disturbances, like floods, also produced statistically significant changes in traffic patterns. These findings underscore the importance of disaggregated, category-wise modelling in transportation planning.

The elasticity analysis reveals that long-run responsiveness to economic indicators is notably higher than in the short run. For example, CPI elasticity reaches 2.52 for large buses in the long run, indicating significant inflation sensitivity in public vehicle demand. Meanwhile, GDP elasticity is highest for light vehicles (1.65), reflecting the strong influence of economic growth on private vehicle demand. These insights are crucial for forecasting demand shifts under financial stress and planning long-term infrastructure investments on key corridors, such as the Jamuna Bridge.

Keywords: *Jamuna Bridge, traffic flow, temporal variation, time series, autoregressive model.*

1. INTRODUCTION

The Jamuna Multipurpose Bridge stands as one of the country's most critical and transformative infrastructure projects. Since its inauguration in 1998, the bridge has significantly improved connectivity between the eastern and western regions of the country, integrating regional economies and fostering national unity (Jenkins & Shukla, 1998).

Over the last two and a half decades, traffic patterns on the Jamuna Bridge have undergone significant changes. This transformation is not only a matter of increased volume but also of the evolving composition of traffic. Multiple factors, including economic growth, changes in fuel prices, toll policies, and external disruptions, potentially influence these changes (Musso et al., 2013). Despite the bridge's strategic importance and sustained operation, a glaring lack of analysis remains to investigate the temporal variation in traffic demand by vehicle type on this infrastructure.

Most existing research in Bangladesh focuses on general traffic forecasts, average daily traffic counts, or congestion studies (Noor et al., 2021). Few studies examine the evolution of traffic patterns over time on major infrastructure, such as national highways or bridges. This presents a critical knowledge gap, particularly in understanding how individual vehicle classes, such as motorcycles, light vehicles, and large buses, respond to policy or economic conditions.

From a policy and planning perspective, this lack of detailed analysis has real-world implications. Infrastructure investment and operational decisions require a strong understanding of traffic demand. Moreover, toll pricing is a significant revenue and policy instrument for infrastructure like the Jamuna Bridge. Adjusting toll rates without understanding the elasticity of demand by vehicle category can be counterproductive.

Bangladesh is undergoing rapid socio-economic transformation. Rising GDP, increasing levels of motorisation, a growing middle class, and shifting patterns of trade and travel are all impacting transportation systems. The lack of integration between traffic volume data and key economic or policy indicators further limits the ability to forecast demand accurately. The impact of external shocks such as the COVID-19 pandemic presents another underexplored area. Limited availability of vehicle-type-specific planning data is also a pressing issue.

Traffic data on the Jamuna Bridge has been recorded monthly for over 25 years by the Bangladesh Bridge Authority (BBA). A thorough analysis, utilising statistical and econometric tools, can reveal long-term trends in traffic demand on this essential infrastructure. It can also demonstrate how specific economic indicators, such as Gross Domestic Product (GDP), inflation, and the Consumer Price Index, influence the demand for bridge use by different vehicle types.

This research will attempt to bridge the research gaps by developing comprehensive time series models that capture the temporal variation of traffic on the Jamuna Bridge across different vehicle categories. The study also incorporates macroeconomic and policy variables into the modelling framework to estimate their influence on traffic demand.

1.1 Research Objectives

The primary goal of this study is to understand how traffic volumes on the Jamuna Bridge have changed over time across three distinct vehicle categories: motorcycles, light vehicles, and large buses. To achieve this goal, the study sets out to accomplish three specific objectives:

i) Analyse the fluctuations in traffic volume by vehicle category using time series data, incorporating GDP, the CPI index, inflation, the number of vehicles registered, and fuel cost as exogenous factors.
ii) Evaluate the effect of external disruptions like the economic crisis and the COVID-19 pandemic on traffic patterns.
iii) Estimate short-run and long-run price elasticities to address the sensitivity of traffic volume to GDP, CPI, and inflation.

1.2 Organisation of this Paper

The rest of the paper is organised as follows. Section 1 provides the background, motivation, and main objectives of the research. Section 2 reviews the relevant existing literature. Section 3 outlines the methodology. Section 4 presents and analyses the results, and Section 5 concludes the study by highlighting the significant findings, contributions, and limitations.

2. LITERATURE REVIEW

This literature review aims to provide a concise overview of the existing research on temporal traffic variations, the economic impacts of traffic, and the influence of external disruptions, such as the COVID-19 pandemic. Additionally, it will provide a critical review of previous work from Bangladesh that has dealt with monthly or yearly traffic variations on national or rural roads, as well as other road infrastructures, such as flyovers.

The exploration of how toll pricing affects travel demand began decades ago, with some of the earliest notable work conducted in the late 1970s and early 1980s (Atkins, 1985; Keeler & Small, 1977). Afterward, researchers like Gifford & Talkington (1996) studied the Golden Gate Bridge in California, USA, and analysed how daily variations in tolls influenced traffic patterns. Stathopoulos & Karlaftis (2001) conducted a seminal investigation in Athens, Greece, and showed that the temporal and spatial variability of urban traffic captures the inherent variability in traffic demand. McMullen & Eckstein (2012) examined the relationship between vehicle miles travelled (VMT) and economic activity in the United States; they found that economic growth generally drives increases in traffic volume, even when there is a temporary economic decline.

In Bangladesh, Sabbir et al. (2022) examined short-term temporal variations in traffic flow across three major flyovers in Dhaka: Mohakhali, Khilgaon, and Jatrabari - by disaggregating vehicles into detailed categories such as motorcycles, cars, buses, and trucks, and by using descriptive data analysis. Ullah et al. (2015) compared traffic growth factors along three national highways: Dhaka-Chittagong, Dhaka-Sylhet, and Dhaka-North Bengal, and found annual growth rates between 11% and 24%, which is higher than the 8-10% used by the Roads and Highways Department (RHD) for structural design.

Hoque et al. (2013) further analysed traffic flow characteristics along the Dhaka-Sylhet Highway (N-2) and identified strong temporal variations, including higher flows on Thursdays and weekends, as well as greater traffic during the rainy season. Their study also relied on descriptive data analysis. Hamid-uz-Zaman (2006) examined traffic flow characteristics on the Nalka-Hatikamrul-Bonpara road using data from the Jamuna Bridge, discovering repetitive flow patterns with notable variations during events such as Eid festivals and strikes, along with a 14% annual growth rate characterised by a heavy dominance of trucks and buses. It is worth noting that none of the above studies have developed models of traffic demand, nor have they attempted to quantify the influence of macroeconomic factors (e.g., GDP, CPI) and socio-economic factors (e.g., pandemics, festivals, natural calamities) on traffic variation. Moreover, none of the above studies were conducted for traffic plying on the Jamuna Bridge.

Therefore, this paper presents one of the first studies to quantify the elasticity of demand for motorcycles, light vehicles, and large buses as a function of different macroeconomic indicators through data analysis and statistical modelling. The model building and elasticity quantification are also supported by a residual diagnosis and a comparison of predicted and observed traffic for three vehicle categories on the Jamuna Bridge.

3. METHODOLOGY

The methodology begins by collecting traffic data, economic indicators (e.g., GDP, CPI, and fuel prices), vehicle registration data, toll rates, and indicator variables for external events. Data is then processed through monthly aggregation, handling missing values, and log transformations. Statistical modelling is conducted using an autoregressive technique to capture both instantaneous and lagged effects. Model evaluation was performed using metrics like adjusted R^2 and residual diagnostics to ensure reliability. Finally, short-run and long-run elasticities are estimated, and the model-predicted traffic values are compared with the observed traffic. Figure 1 presents a structured methodology for analysing the temporal variation of traffic on the Jamuna Bridge.

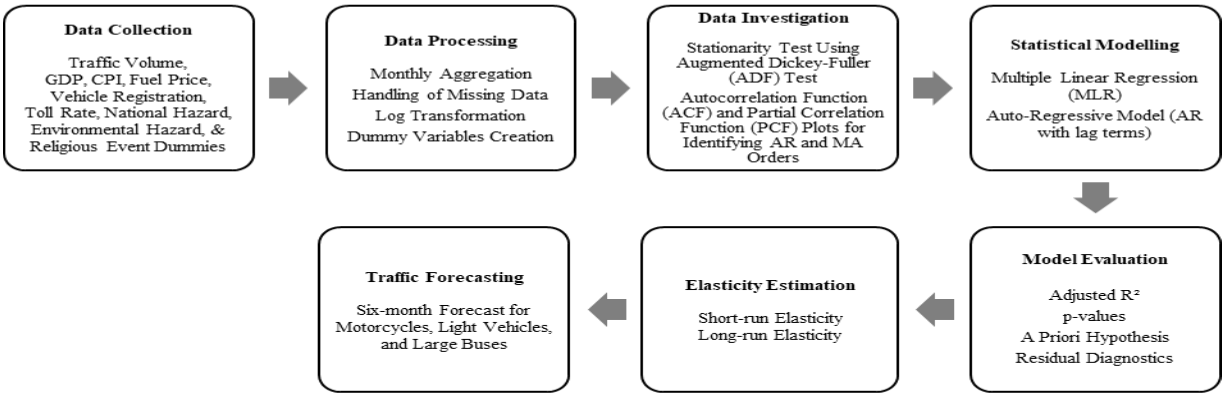


Figure 1: Overview of Methodology

3.1 Data Collection

3.1.1 Traffic Volume Data

Traffic volume data by vehicle category were obtained from the Bangladesh Bridge Authority (BBA) through special permission, since the data is not currently available for public use. The data include monthly traffic counts categorized into (i) motorcycles, (ii) motor vehicles, and (iii) large buses.

The dataset spans from July 1998 to December 2023, offering 25 years of traffic volume history that is ideal for time series analysis. For modelling purposes, the dataset was aggregated to monthly totals for each vehicle category, providing an interpretable temporal series. A total of 300 monthly data points for each vehicle category, spanning from July 1998 to June 2023, were utilized for model building, with the data from the last six months of 2023 reserved for forecasting.

3.1.2 Exogenous Economic Variables

Multiple exogenous variables have been curated for model building. Table 1 presents the name, description, and source of each variable.

Table 1: Descriptions and Variables Used in the Study

Variables	Description	Sources
Dependent variable	Traffic volume of each vehicle category.	Bangladesh Bridge Authority (Not publicly available).
GDP	Annual Gross Domestic Product (in constant prices).	World Bank (2024). World Bank Open Data.
CPI	Monthly Consumer Price Index.	World Bank (2024). World Bank Open Data.
Inflation	Annual average inflation rate (%).	World Bank (2024). World Bank Open Data.
Fuel Price	Monthly price of diesel per liter (in BDT).	World Bank (2024). World Bank Open Data.
Vehicle Registration	Monthly count of newly registered motor vehicles.	Bangladesh Road Transport Authority (BRTA, 2024).
Toll Rates	Toll history by vehicle category (monthly).	Bangladesh Bridge Authority (BBA).
Indicator Variables	To capture COVID-19 lockdowns, toll changes, Eid holidays, and floods.	Government press releases, BBA, media archives.

3.2 Model Development

The mode development started with the estimation of an ordinary multiple linear regression (OMLR) model to understand the direction of impact of various economic and external factors on traffic volume. However, OMLR is not suitable for identifying variation in time series data due to the violation of the independence assumption. Hence, the OMLR exploration was followed by the development of an autoregressive model. Nonetheless, the autoregressive model building was preceded by appropriate investigative tests, such as the (i) test for stationarity, and (ii) identification of moving average (MA) and autoregressive (AR) orders using autocorrelation factor (ACF) and partial autocorrelation factor (PACF) plots. Equation (1) presents the generic model formulation used for three vehicle categories. Please note that the final model form of the three-vehicle category varied from the generic form depending on the statistical significance of different parameter estimates. A logarithmic transformation of the dependent and independent variables was used for model building; as a result, the estimated coefficients can be directly interpreted as elasticities.

$$logY_t = \gamma_0 + \gamma_1\, log(GDP_t) + \gamma_2\, log(CPI_t) + \gamma_3\, log(FP_t) + \gamma_4\, log(VR_t) + \gamma_5\, log(INF_t) + \alpha(logY_{t-1}) + \sum \delta_K\, D_K + \varepsilon_t \quad (1)$$

Where,

$logY_t$ = Log of traffic volume at time t

γ_0 = Constant term

$log(GDP_t)$ = Log of gross domestic product at time t

$log(CPI_t)$ = Log of consumer price index

$log(FP_t)$ = Log of fuel price

$log(VR_t)$ = Log of vehicle registration

$log(INF_t)$ = Log of inflation rate

$log(Y_{t-1})$ = First-order autoregression term

D_K = k number of dummy variables

ε_t = Error term

3.3 Elasticity Calculation

Short-run elasticity measures the immediate or instantaneous response of traffic volume to a change in an explanatory variable (such as GDP, CPI, or inflation), assuming other factors remain constant.

Long-run elasticity, on the other hand, captures the adjustment of traffic volume over time in response to a sustained change in a variable. Long-run elasticities are typically larger in absolute value than short-run. In this study, a log-log autoregressive framework is employed, in which the estimated coefficients directly represent short-run elasticities; i.e., the estimated parameters can be interpreted as the percentage changes in traffic volume resulting from a 1% change in the independent variable. On the other hand, the long-run elasticity is calculated by adjusting the estimated parameter for the effect of the lag, using equation 2 below:

$$\text{Long-run Elasticity} = \frac{\gamma_i}{1-\alpha} \quad (2)$$

Where,

γ_i = Estimated coefficient for explanatory variables like toll, GDP, CPI

α = Coefficient of the lagged dependent variable $log(Y_{t-1})$

4. RESULTS AND DISCUSSION

4.1 Trend Analysis by Vehicle Category

This section presents the general trend in the vehicle growth on the Jamuna Bridge for motorcycles, light vehicles, and large buses. Non-stationarity in time series data refers to the condition where the statistical properties, such as mean, variance, and autocorrelation, change over time. This poses a significant problem because most time series model, including autoregressive integrated moving average (ARIMA) models, assume that the data is stationary. The Augmented Dickey-Fuller test (ADF) was conducted to test the stationarity of all the time series. The null hypothesis of non-stationarity is rejected if the p-value of the test statistic is sufficiently small.

4.1.1 Motorcycle

Figure 2 illustrates monthly motorcycle traffic across the Jamuna Bridge from 1998 to 2023. The figure shows a clear long-term upward trend with distinct phases of growth.

From the late 1990s until around 2010, the volume of motorcycles remained relatively low and stable. A gradual increase became evident after 2010, gaining momentum around 2015, and accelerating significantly post-2018. In 2021, motorcycle counts reached their peak, potentially due to post-lockdown travel surges.

The ADF test on the log-transformed motorcycle series yielded a test statistic of -3.931 with an associated p-value of 0.012. Hence, the null hypothesis was rejected, and the log-transformed series was found to be stationary.

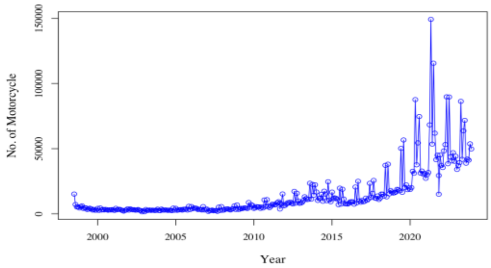


Figure 2: Flow Fluctuations of Motorcycles During the Years 1998 to 2023

4.1.2 Light Vehicle

Figure 3 illustrates a steady and consistent increase in light vehicle traffic from 1998 to 2023.

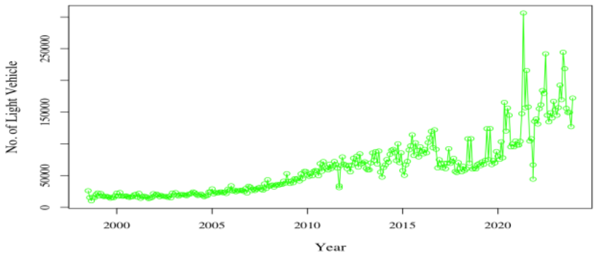


Figure 3: Flow Fluctuations of Light Vehicles During the Years 1998 to 2023

In the early years, up to around 2010, the number of light vehicles using the bridge grew gradually, reflecting stable conditions and moderate growth in vehicle ownership. A noticeable surge occurred after 2019, likely due to an increased preference for private transport during the COVID-19 pandemic, as well as improvements in purchasing capacity and urban expansion.

The ADF test on the log-transformed light vehicle series yielded a test statistic of -3.982 with an associated p-value of 0.010. Hence, the null hypothesis was rejected, and the log-transformed series was accepted as stationary.

4.1.3 Large Bus

Figure 4 illustrates the growth in large bus traffic from 1998 to 2023, demonstrating a steady and consistent upward trend over the years.

In the early 2000s, the number of large buses crossing the bridge was relatively low. Still, it gradually increased due to the expansion of long-distance bus services and greater reliance on public transport. Sharp drops are visible around 2020 and 2021, which may be linked to travel restrictions during the COVID-19 pandemic. Despite occasional dips, the overall trend remains positive, indicating the continuing importance of bus transport for passenger mobility across the Jamuna Bridge.

The ADF test on the log-transformed large bus series yielded a test statistic of -3.945 with an associated p-value of 0.012. Hence, the null hypothesis was rejected, and the log-transformed series was accepted as stationary.

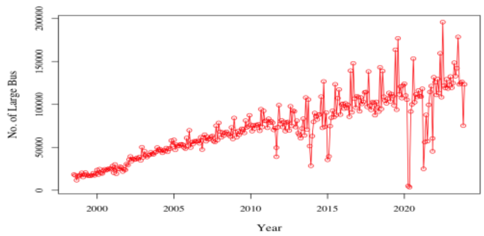


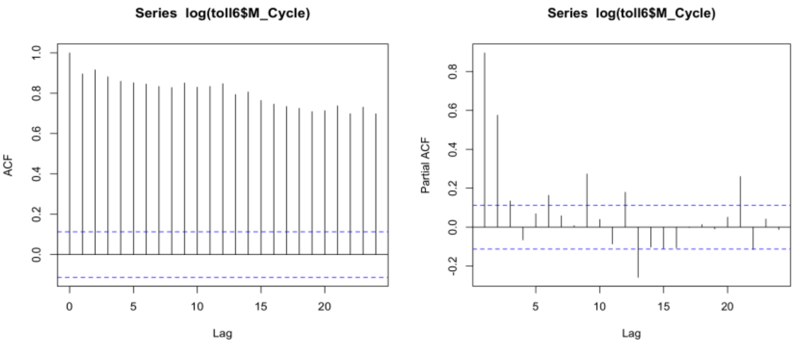
Figure 4: Flow Fluctuations of Large Buses During the Years 1998 to 2023

4.2 ACF and PACF Diagnostics for Model Specification

Next, the three log-transformed series were investigated for the moving average (MA) and autoregressive (AR) orders using autocorrelation (ACF) and partial autocorrelation (PACF) plots.

4.2.1 Motorcycle

For the motorcycle series, the ACF plot exhibits a gradual decay, while the PACF plot displays a sudden cutoff after lag 2. So, the model could be an AR (2) model.

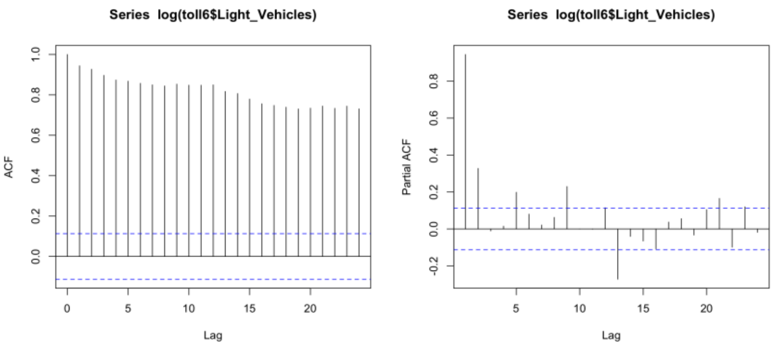


(a) (b)

Figure 5: (a) ACF Plot and (b) PACF Plot of Motorcycle

4.2.2 Light Vehicle

For the light vehicle series, the ACF plot shows a gradual decay, and the PACF plot shows a sudden cut-off after lag 2. So, the model could be an AR (2) model.

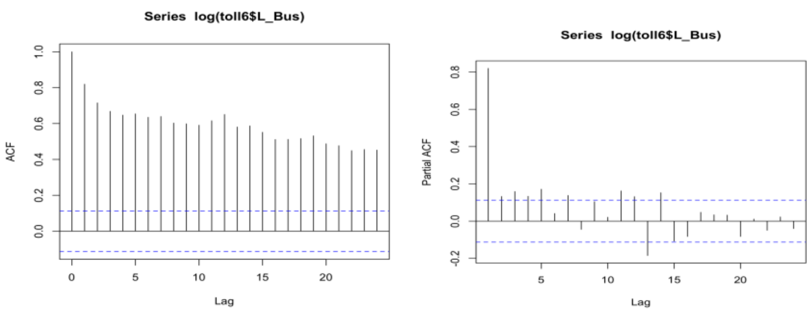


(a) (b)

Figure 6: (a) ACF Plot and (b) PACF Plot of Light Vehicle

4.2.3 Large Bus

For the large bus, the ACF plot exhibits a gradual decay, while the PACF plot displays a sudden cutoff after lag 1. Therefore, the model could be an AR (1) model.



(a) (b)

Figure 7: (a) ACF Plot and (b) PACF Plot of Large Bus

Considering the limited number of data points in the three series, and model parsimony, this study chooses the first-order AR (1) autoregressive model for motorcycle, light vehicle, and large bus.

4.3 Model Estimation by Vehicle Category

This section presents the results of autoregressive models with exogenous variables – often referred to as the ARX model in the literature. Due to space constraints, multiple linear regression models are not reported. It can be noted that various models were built based on a priori hypotheses, and the final models were selected based on the sign and magnitude of parameters and the overall goodness-of-fit measure, such as the adjusted R-squared. The final model results are reported below separately for the three vehicle types.

4.3.1 Motorcycle

From Table 2, it can be observed that the adjusted R-squared value for the motorcycle series is 0.868, based on 302 training observations and 8 model parameters, indicating a strong fit and commendable explanatory power of the selected exogenous variables.

Table 2: Estimated Demand Equation for Motorcycle

Fit Indices			
Adjusted R^2	0.8676		
Model Estimate (No. of training data: 302 data)			
Variables	**Coefficient**	**Std. error**	**t-statistic**
Log (CPI)	0.334	0.129	2.59
Log (Lagged Traffic)	0.264	0.064	4.15
Toll Price change indicator 1	1.179	0.058	20.50
Toll Price change indicator 2	1.212	0.109	11.05
Full lockdown indicator	1.098	0.193	5.70
Partial lockdown indicator	0.756	0.121	6.27
Eid festival indicator	0.383	0.072	5.31
Flood indicator	0.332	0.124	2.68

The COVID-19 lockdowns had a pronounced positive impact. Both complete lockdown and partial lockdown are strongly significant. These findings reflect a shift in modal preference towards motorcycles during the pandemic, likely driven by the need for safer, socially distanced personal mobility. Eid festivals also contributed to a significant rise in motorcycle traffic. Flood events were associated with a substantial increase in motorcycle traffic. Overall, motorcycle traffic on the Jamuna Bridge is minimally influenced by macroeconomic indicators, such as GDP and inflation, but is strongly driven by cost-related pressures (CPI), previous usage trends, and external disruptions, including lockdowns, festivals, and floods.

4.3.2 Light Vehicle

From Table 3, the adjusted R-squared value of 0.851 for light vehicles, with 302 training observations and 07 parameters, reflects a strong model fit with substantial explanatory power of the exogenous variables.

Table 3: Estimated Demand Equation for Light Vehicles

Fit Indices			
Adjusted R^2	0.8507		
Model Estimate (No. of training data: 302 data)			
Variables	**Coefficient**	**Std. error**	**t-statistic**
Log (GDP)	0.198	0.121	1.64
Log (CPI)	0.696	0.103	6.78
Log (Lagged Traffic)	0.341	0.079	4.29
Toll Price change indicator 1	0.876	0.046	19.01
Toll Price change indicator 2	0.929	0.088	10.61
Full lockdown indicator	0.316	0.155	2.04

Eid festival indicator	0.208	0.049	4.22

For light vehicles, GDP (Log-transformed) shows a positive but statistically less significant effect on light vehicle traffic, indicating that growth in national economic output does not reliably predict fluctuations in light vehicle usage. The Consumer Price Index (CPI) demonstrates a strong, positive, and statistically significant impact, suggesting that as the prices of consumer goods and services rise, light vehicle travel also increases. The lagged traffic variable is also essential, indicating that past traffic volumes strongly predict current usage. Toll price changes had a significant and positive effect, suggesting that light vehicles remained affordable and essential despite toll hikes. The impact of the COVID-19 complete lockdown Indicator is moderately positive and statistically significant, indicating a rise in light vehicle traffic during the stricter phase of the pandemic. Eid festivals significantly boosted light vehicle traffic. This result reflects heightened travel demand during festival periods, as people visit relatives or travel for celebrations.

4.3.3 Large Bus

From Table 4, it can be noticed that, with an adjusted R-squared value of 0.701, the model for large buses demonstrates a reasonably good fit. However, it leaves more variation unexplained compared to models for other vehicle types.

Table 4: Estimated Demand Equation for Large Bus

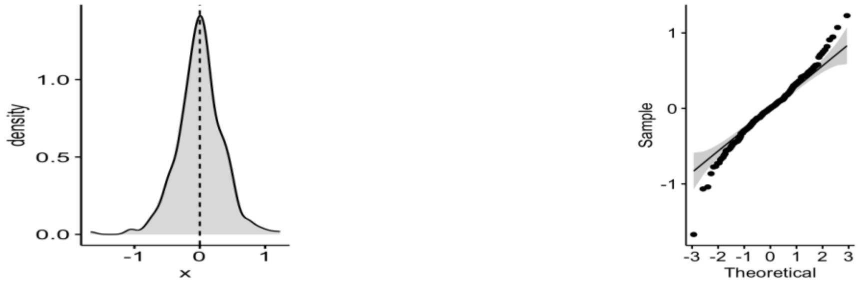
Fit Indices			
Adjusted R^2	0.7006		
Model Estimate (No. of training data: 302 data)			
Variables	**Coefficient**	**Std. error**	**t-statistic**
Log (CPI)	1.439	0.121	11.88
Log (Lagged Traffic)	0.427	0.055	7.79
Toll Price change indicator 1	0.334	0.054	6.14
Toll Price change indicator 2	1.053	0.103	10.19
Full lockdown indicator	-1.362	0.182	-7.47
Partial lockdown indicator	-0.859	0.113	-7.59
Eid festival indicator	0.085	0.054	1.57
Flood indicator	-0.169	0.116	-1.46

For large buses, the CPI (Consumer Price Index) exhibits a strong, positive, and highly significant effect. This suggests that as consumer prices rise, large bus traffic increases substantially. The lagged traffic variable is also statistically significant, indicating strong temporal consistency in large bus usage. COVID-19 lockdowns had a substantial negative impact on large bus traffic. These results are expected, as bus services were heavily restricted during the pandemic. The Eid festival indicator had a positive but statistically moderately significant effect, indicating that bus traffic may have risen slightly during Eid. Flood events were associated with a statistically moderate but negative change in bus traffic.

4.4 Residual Analysis

The diagnostic test of the residuals followed the model building. The normality of residuals was examined for each vehicle category to validate the assumption of homoscedastic and non-correlated errors. The asymptotic one-sample Kolmogorov-Smirnov test and the Pearson Chi-Square normality test were conducted with the null hypothesis that the distribution of the residuals is normal. A p-value greater than 0.05 indicates that the null hypothesis of normality could not be rejected.

The findings from the tests are supported by the density plots and Q-Q plots presented in Figure 8, where no significant asymmetry or deviation from the diagonal line is observed. Due to the space limitation, the density plot is only shown for the motorcycle series.



(a) (b)

Figure 8: (a) Density Plot and (b) Q-Q Plot of Motorcycle Residuals

4.5 Elasticity Estimation

The elasticity estimates presented in Table 5 offer key insights into how traffic volumes across different vehicle categories respond to changes in macroeconomic indicators, including GDP, CPI, and inflation. The three rows for which the estimated parameters were moderately significant have been marked in grey.

Table 5: Estimated Short-run and Long-run Elasticity

Vehicle Category	Variables	Short-run elasticity	Long-run elasticity
Motorcycle	GDP elasticity	0.047	0.065
	Inflation elasticity	-0.026	-0.036
	CPI elasticity	0.033	0.458
Light vehicle	GDP elasticity	0.198	1.655
	CPI elasticity	0.696	1.048
Large Bus	GDP elasticity	0.026	0.045
	CPI elasticity	1.439	2.516

For the motorcycle from Table 4.4, it can be noticed that GDP Elasticity is very low in both the short run and long run, indicating an inelastic response of the motorcycle to macroeconomic indicators. The CPI elasticity is moderately positive, particularly in the long run, indicating that a 1% increase in the CPI will result in a 0.46% increase in motorcycle traffic on the Jamun Bridge.

For light vehicles, the GDP elasticity is moderate in the short run. Still, it rises substantially in the long run, suggesting that a 1% increase in GDP will result in more than a 1% increase in light vehicle traffic on the Jamuna Bridge in the long run.

For large buses, CPI elasticity is the strongest, especially in the long run, indicating that a 1% increase in the CPI will result in a more than 2.5% increase in the bus population on Jamuna Bridge.

4.6 Future traffic forecast

To assess the practical applicability of the developed time series models, a six-month forecast (July 2023 to December 2023) of traffic volume was carried out for each of the three vehicle categories: motorcycles, light vehicles, and large buses. The models used for this forecast are the best-fit autoregressive (ARX) models presented in section 4.3 of the paper.

4.6.1 Motorcycle

The graph shown in Figure 9 compares the observed and predicted motorcycle traffic volumes on the Jamuna Bridge over six future monthly observations, presented on a logarithmic scale. It can be noted that the expected trend closely matches the observed trend, with notable declines in the 2nd and 6th months, and a mild upward trend between the second and fifth months. However, in general, the predicted traffic underestimates the observed traffic by approximately 30%.

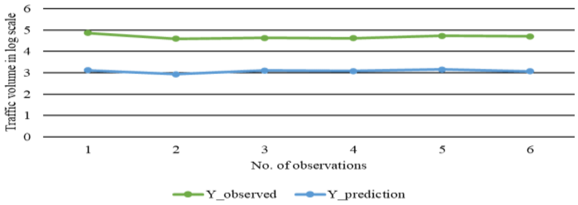


Figure 9: Predicted vs Observed Motorcycle Traffic on Jamuna Bridge

4.6.2 Light Vehicle

Figure 10 presents a comparison of the predicted and observed light vehicle traffic over six months. The light vehicle traffic seems to have milder variation during the six months than the motorcycle traffic. Nonetheless, the predicted series appears to capture the decline in the second month and the stable periods between the 3rd and 4th months. However, in this case also, the prediction is always lower than the observed traffic by a margin of roughly 35%.

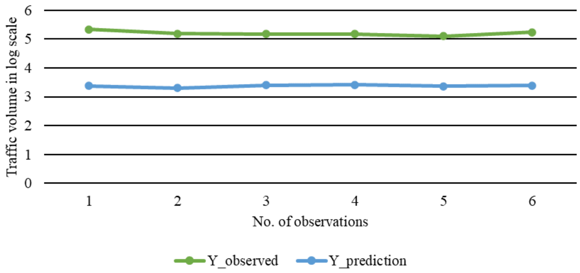


Figure 10: Predicted vs Observed Light Vehicle Traffic on Jamuna Bridge

4.6.3 Large Bus

Figure 11 compares the predicted large bus with the observed large buses. The prediction for the large bus is much closer to the observed values, with a margin of error of only around 15%, and the predicted trend closely matches the observed trend.

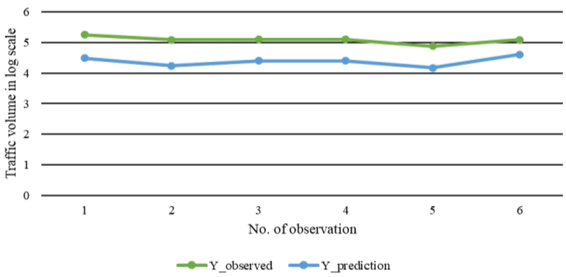


Figure 11: Predicted vs Observed Large Bus Traffic on Jamuna Bridge

5. CONCLUSIONS

This study undertakes a detailed examination of temporal variations in traffic flow across the Jamuna Bridge by employing an autoregressive time series modelling technique. To the best of the authors' knowledge, this is the first study to model the traffic pattern as a function of macroeconomic (e.g., GDP, CPI) and socio-economic indicators, including pandemics, festivals, and natural calamities. The study separately quantifies the short and long-run demand elasticities of motorcycles, light vehicles, and large buses. The estimated elasticities indicate that the motorcycle demand is the least elastic, followed by the private vehicle demand. The demand for large buses was found to be the most elastic with respect to CPI. The highest GDP elasticity was noted for light vehicles in the long run.

It is worth noting that the primary objective of the study was to quantify the demand elasticities of different vehicle categories. Nonetheless, a comparison of the predicted future traffic with the observed trends is also included for completeness. The models attributed moderate predictive accuracy (margin of error varied from 10% to 35%), because the time series covered only 25 years. Future studies could explore more advanced techniques for obtaining better predictive accuracy, such as the long- and short-term memory models, given the availability of larger time series.

DECLARATION OF USE OF AI

In this paper, AI (Grammarly) is used for grammar and spelling checks; however, the initial and final drafts were written by the authors only.

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