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TRAFFIC FLOW PREDICTION PERFORMANCE COMPARISON BETWEEN ARIMA AND MONTE CARLO SIMULATION

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Abstract:
Time series analysis and forecasting has become a major tool in numerous applications. It has the analysis and forecasting capacity of long term, intermediate term and short-term prediction. Monte Carlo simulation is also another reliable name for forecasting in the simulation world. In this paper Monte Carlo simulation and time series Box-Jenkins ARIMA model (Autoregressive Integrated Moving Average) model are implemented to figure out the missing data points with full range traffic flow forecasting. As ARIMA deviates on non-seasonal data points or abrupt standard deviation, this two are used to find out the capacity of forecasting on those issue. Here using the traffic volume of previous 75% of a day, the least 25% traffic volume is forecasted. Then it is compared with the actual data. The ACF and PACF are plotted and checked the best model of fit for this data. The mean absolute relative error (MARE) and mean absolute percentage error (MAPE) are calculated and it is 8.51% and 2.19% respectively for time series and MAPE was found 6.66% with Monte Carlo simulation. ARIMA gives a nice forecast overall but fails at abnormal changing points whereas Monte Carlo overcomes this problem and suggests all probable possibilities.

1 INTRODUCTION

With the prospective development in the transportation system, a new term called Intelligent Transportation System (ITS) has been introduced nowadays and practically used largely to improve the efficiency, safety, and productivity of the surface transportation system. The Intelligent Transportation System (ITS) integrates the advanced information technology with data communication technology, electronic technology, sensor technology, and computer processing technology which can bring great convenience for people's travels showing the distribution characteristics and providing short-term traffic flow forecasting. However, the traffic system is a random system with strong uncertainty and complexity. A large number of uncertain factors cause short-term traffic flow to highly complex nonlinear characteristics. For these reasons, it's difficult to improve the precision of single prediction mode or to expand the scope of application which results in different combined forecasting models with different advantages. At the same time, it is also essential to understand the working process behind all these methods to get an idea about the stability, reliability and the limitations associated with each of them.

Prediction science is generating importance day by day. It is now practiced in various fields for the convenience of human being's day to day task. Long term forecasts are used for system planning, scheduling construction of new generation capacity and purchasing of generating units (Al-Hamadi *et al.,* 2005) [2]. Intermediate-term forecasts which are also called medium-term forecast are used for maintenance scheduling, coordination of load dispatching and fixing of prices, so that demand can meet with original capacity (Zhang *et al.*, 2012) [17]. Adding with that, forecasting of next hours passengers of a station, a number of approaching vehicles at next minute which is known as short term prediction is becoming popular because of the need of fewer data to forecast. Short-term forecasts are used for optimal generator unit commitment, fuel allocation, maintenance scheduling and buying and selling of power, economic scheduling of generating capacity, scheduling of fuel purchases, security analysis and short-term maintenance scheduling (A. Hasnat & F.I. Rahman, 2019) [16]. Very short term forecast is used for security assessment and economic dispatching, real-time control and real-time security evaluation (Sigauke *et al*., 2011) [14]. The four main categories of time horizons have been studied extensively. In case of long term forecasts Al-Saba *et al*.(1999) [1], Kermanshashi (2002) [8] and Carpinteiro *et al*. (2007) used Artificial Neural network (ANN) [8]; intermediate-term forecasts by Elkateb *et al*. (1998), Mirasgedis *et al*. (2006) [11] and Tsekouras *et al*. (2007). They also used Artificial/Fuzzy Neural Network for forecasting; short-term forecasts by Al-Hamadi and Soliman (2004) based on Kalman filtering algorithm [2], Hobbs *et al*. (1998) and Catalao *et al*. (2007) based on neural network approach and A. Hasnat & F.I. Rahman (2018) on Monte Carlo simulation [4]; very short term forecasts by Taylor (2008) and Taylor *et al*. (2008) [15].

Several forecasting methods including multiple linear regression Al-Hamadi (2005) [2], Amjady and Keynia (2011) [3], K. Prabakaran *et al*. (2013) [10] and Mirasgedis *et al*, (2006) [11]; nonlinear multivariable regression model by Al Rashidi and El-Naggar (2010), Tsekouras *et al*. (2007) and Suwardo *et al*. (2010) [13] are implemented for different types of forecasting and varying degrees of success based on multiple type data.

In case of the practical need of knowing the number of vehicles approaching in different hours of a busy road, short term traffic flow has gained great attention compared to others. As the accuracy of prediction affects the maintaining capacity of traffic operation that results in a great traffic jam. Since maintaining the appropriate load of traffic is crucial for the city it is extremely essential to forecast an accurate traffic flow. That is why time series ARIMA model has been implemented here. Since different time series models have different characteristics with different types of data sets [6], here it has been tried to find out the possibility and limitations of ARIMA model in short term prediction on this semi-seasonal, non-stationary data.

Monte Carlo simulations are used to model the probability of different outcomes in a process that cannot easily be predicted due to the intervention of random variables. It is a technique used to understand the impact of risk and uncertainty in prediction and forecasting models. A. Hasnat and F.I. Rahman (2018) [4] showed that the simulation has a high impact on traffic flow forecasting. Monte Carlo simulation is also used here for short term traffic flow prediction on semi-seasonal stationary data to find out the reliability of the forecasting comparing with time series analysis. The result has been found quite amazing. At last, the result from time series analysis and Monte Carlo simulation are compared.

2 METHODOLOGY

2.1 Study location and data collection

The data worked out here have been found from the Transport Infrastructure Ireland (TII). The traffic volume used here is from the link road between junction-1 and junction2 of Dublin Airport route, Ireland from January 31, 2018, to February 03, 2018 (Fig.1).

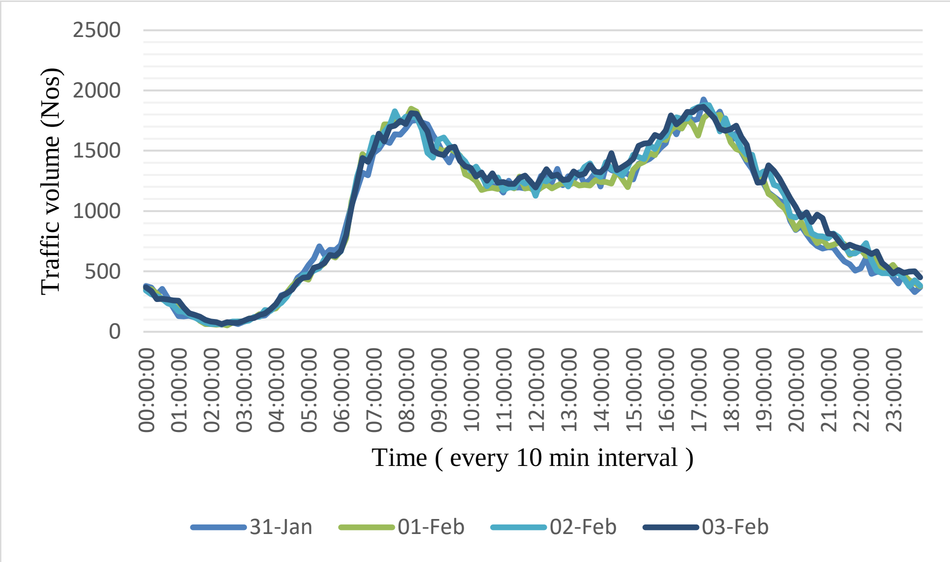


***Fig 1**. Observed original traffic volume with respect to time*

2.2 Time series analysis: In this paper, the Box-Jenkins ARIMA model has been implemented to forecast traffic volume [5]. Here the type of forecast accomplished is using 75% data of 31 January and forecasted the least 25% of the same day. And then the forecasted value is compared to the original value of 31 January. Another type of forecasting can be done through the same procedure which is the prediction of 01 February whole day volume using the total volume of 31 January. Here also the forecasted value should be compared with the real one.

To fit the non-seasonal Box-Jenkins ARIMA model for a stationary time series data there are some steps. The forecasting follows directly from the fitted model. The general form of ARIMA (p,d,q) model can be represented as: $Z_t = Ø_1 Z_{t-1} + Ø_2 Z_{t-2} + \dots\dots + Ø_p Z_{t-p} - θ_1 ε_{t-1} + θ_2 ε_{t-2} + \dots\dots\dots + θ_q ε_{t-q} + ε_t$;

Where, Z $_t$ is the value of a stationary time series at time t and ε_t's represent random error which is being independently and normally distributed with zero mean and constant variance for time t = 1, 2…..n. 'p' is for autoregressive order; 'd' is a number of differencing and 'q' is the moving average order; Ø's and θ's are coefficients to be estimated.

2.2.1 Model identification

The order of the model is identified based on time domain and frequency domain analysis i.e. autocorrelation function (ACF), partial autocorrelation function (PACF) and spectral density function. A graph of autocorrelation function determines whether the series is stationary or not. The time series is considered stationary if the graph of ACF values either cuts off fairly quickly or dies down fairly quickly. The series is considered as non-stationary if the graph of ACF dies down extremely slowly. In case of the non-stationary series, it can be converted to a stationary series by successive differencing (Fig.2). Besides the stationarity can also be checked by trend analysis through mean and variance (Table1). In this case, the 1st difference of log(flow) gives almost zero mean and 1st difference of log(flow) gives most smaller variance. So, ACF and PACF graph are plotted considering d(log(flow)) of data(Fig.3)

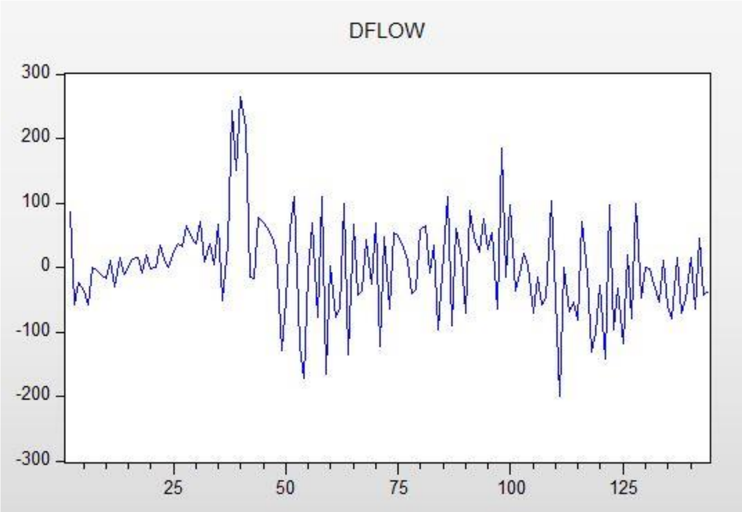
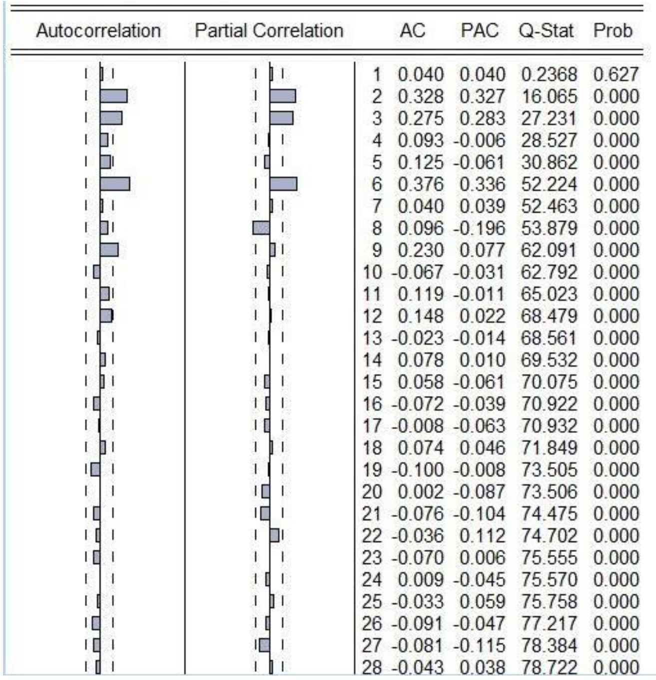


Fig2. *Graph of the data after 1st difference (Stationarity check)*

After the 1st difference, the mean of the data turns to almost zero and the variance is nearly constant (Table 01) and the trend is almost invisible (Fig.2). So, there is no need for more difference. Thus the difference order becomes '1'.

Tab 1. *Stationarity analysis of data*

	Mean	**Variance**
flow	928.97	289130.03
d(flow)	0.5734	5638.7201
log(flow)	6.5082	0.9622505
d(log(flow))	0.0024	0.0144999



Lag	AC	PAC	Q-Stat	Prob
1	0.040	0.040	0.2368	0.627
2	0.328	0.327	16.065	0.000
3	0.275	0.283	27.231	0.000
4	0.093	-0.006	28.527	0.000
5	0.125	-0.061	30.862	0.000
6	0.376	0.336	52.224	0.000
7	0.040	0.039	52.463	0.000
8	0.096	-0.196	53.879	0.000
9	0.230	0.077	62.091	0.000
10	-0.067	-0.031	62.792	0.000
11	0.119	-0.011	65.023	0.000
12	0.148	0.022	68.479	0.000
13	-0.023	-0.014	68.561	0.000
14	0.078	0.010	69.532	0.000
15	0.058	-0.061	70.075	0.000
16	-0.072	-0.039	70.922	0.000
17	-0.008	-0.063	70.932	0.000
18	0.074	0.046	71.849	0.000
19	-0.100	-0.008	73.505	0.000
20	0.002	-0.087	73.506	0.000
21	-0.076	-0.104	74.475	0.000
22	-0.036	0.112	74.702	0.000
23	-0.070	0.006	75.555	0.000
24	0.009	-0.045	75.570	0.000
25	-0.033	0.059	75.758	0.000
26	-0.091	-0.047	77.217	0.000
27	-0.081	-0.115	78.384	0.000
28	-0.043	0.038	78.722	0.000

Fig3. *ACF and PACF analysis (using EVIEWS software)*

Therefore, based upon the conditions of values and graphical plot of ACF and PACF, it follows the following tentative ARIMA(p,d,q) models shown in table 2. To select the best suitable model for forecasting out of the models proposed, the lowest BIC (Bayesian Information Criterion) and AIC (Akaike Information Criterion) values are needed. It is found that the ARIMA(6,1,0) shows the smallest AIC and BIC value among other proposed models (Table 2). Thus ARIMA(6,1,0) is considered as the best model of fit for this data and the forecasting is carried out using this fit.

Tab 2. *AIC and BIC values of fitted ARIMA model*

		ARIMA Model						
		(2,1,0)	**(0,1,2)**	**(3,1,0)**	**(0,1,3)**	**(6,1,0)**	**(2,1,2)**	**(0,1,6)**
Co efficients	AR(1)	0.08		-0.04		-0.08	0.08	
	AR(2)	0.32		0.36		0.31	0.32	
	AR(3)			0.24		0.20		
	AR(4)					-0.006		
	AR(5)					-0.08		
	AR(6)					0.31		
	MA(1)		-0.09		-0.01		0.098	0.036
	MA(2)		0.56		0.53		0.566	0.414
	MA(3)				0.13			0.069
	MA(4)							0.032
	MA(5)							0.093
	MA(6)							0.563
	Log-Likelihood	100.80	101.75	106.10	102.37	121.78	101.275	111.37
	AIC	-1.55	-1.54	-1.63	-1.53	**-1.88**	-1.54	-1.63
	BIC	-1.48	-1.47	-1.54	-1.44	**-1.72**	-1.47	-1.47

2.2.2 Model estimation

ARIMA fitting order p, d, q values and their statistical significance can be judged by t-distribution. A model with minimum values of RMSE, MAPE, AIC, BIC, Q-statistics and with high R-square, may be considered as an appropriate model for forecasting. The model selection criteria include Akaike Information criterion (AIC) and Schwarz's Bayesian Information Criterion (BIC), Mean squared error (MSE), Root Mean squared error (RMSE), Mean absolute error (MAE) and Minimum Absolute Percentage Error (MAPE)

2.2.3 Diagnostic checking

It is necessary to ensure the residuals estimated from the model are white noise. So the autocorrelations of the residuals are to be estimated for the diagnostic checking of the model. These may also be judged by Ljung-Box statistic under the null hypothesis that autocorrelation co-efficient is equal to zero. Moreover, it can also be checked that the properties of the residual with the graph as follows.

1) Check the normality by considering the normal probability plot or the p-value from the One-Sample Kolmogorov – Smirnov Test.

2) Check the randomness of the residuals by considering the graph of ACF and PACF of the residual. The individual residual autocorrelation should be small and generally within ± 1.96/ N of zero.

2.2.4 Forecast

ARIMA models are developed basically to forecast the corresponding variable. The entire data is segregated in two parts, one for sample period forecasts and the other for post-sample period forecasts. Frequency domain analysis is one of the first analytical techniques developed by Koreisha and Fung (1999) and Pankratz (1983). It is also known as periodogram analysis. Evaluation of forecasting found from the periodogram analysis was performed by using mean absolute relative error (MARE) and mean absolute percentage prediction error (MAPPE).

2.3 Monte-Carlo simulation: Monte Carlo simulations are used to model the probability of different outcomes in a process that cannot easily be predicted due to the intervention of random variables. It is a technique used to understand the impact of risk and uncertainty in prediction and forecasting models.

Periodic flow = ln (present actual flow/previous flow value)

Next calculated the AVERAGE, STDEV.P, and VAR.P functions on the entire resulting series to obtain the average periodic flow, standard deviation, and variance inputs, respectively. The drift is equal to:

Drift = average periodic flow – (variance/2)

Alternatively, drift can be set to 0; this choice reflects a certain theoretical orientation, but the difference will not be huge, at least for shorter time frames. After that to obtain a random input:

random value = standard deviation * NORMSINV(RAND())
next 10 min forecast = present actual flow * e ^ (drift + random value)

Here, every 10 min data of three days (31 Jan, 01 Feb, 03 Feb) is taken into consideration for calculation and made simulation 100 times each for forecasting of Feb 03. Thus total 144*100=14400 simulations are done to obtain the result. After calculating the average of every 10 min flow from 14400 simulations the forecast is gotten. Then the forecasted value for Feb 03 is compared with the actual value of Feb 03. The result is quite amazing.

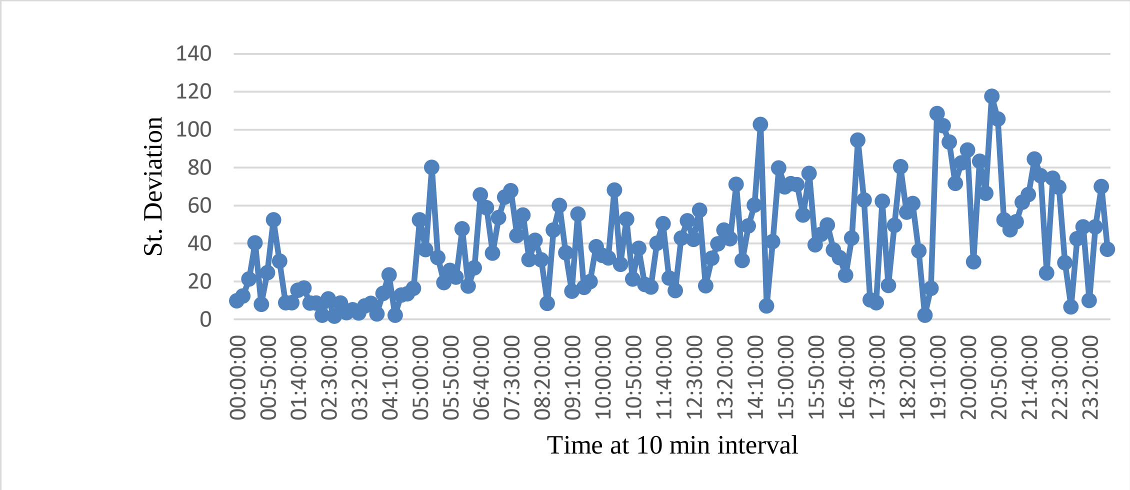


Fig4. *Standard Deviation vs. Time graph*

3 RESULT AND DISCUSSIONS

Dublin airport link road is one of the busiest roads of Ireland. This road is so important as 133773 vehicles in average use this road every day. So, knowing the number of vehicle moving at every minute is important for traffic operation for the authority and knowing the volume of traffic of upcoming hours play a vital role to take effective measures. Different methods and models are now practised for the forecast of traffic volume according to different types of data. When it comes to a critical condition where traffic forecast is mandatory but the data is limited then there short term forecast is needed to apply. Here short term traffic flow prediction model such as ARIMA model is fitted with limited input of data. And a simulation model named Monte Carlo simulation is also used to predict the traffic volume. The goal is to compare the result of Time Series Analysis with Simulation method. As there is short term data, so using the data of 75% time of the day, the least 25% is predicted here. The prediction scenario is shown in (Fig.4).

3.1 Time series analysis:

Here using the data of 00:00:00 to 21:10:00, the least 21:20:00 to 23:40:00 are predicted using the Box-Jenkins ARIMA(6,1,0) model and the forecasted data is compared with original data to measure the errors (Table 3) The performance of the model is measured by the degree of accuracy. Accuracy of the model is indicated by statistical closeness such as mean absolute relative error (MARE) and mean absolute percentage predicting error (MAPPE). Both are an indicator of model performance. The model which has a minimum value of MARE and MAPPE is the accurate model (the best) among the several tentative models in predicting. In another word, the minimum residual (error) indicate high accuracy model.

Tab 3. *Forecasting and Forecasted Error calculation*

Time	Original data	Forecasted	MARE	MAPE
21:20:00	681	706.4292	1.69528	0.24894
21:30:00	681	678.7646	0.149025	0.02188
21:40:00	679	697.1039	1.206925	0.17775
21:50:00	654	673.8079	1.320525	0.20191
22:00:00	600	698.0589	6.537262	1.08954
22:10:00	610	675.4425	4.3628	0.71521
22:20:00	549	675.7625	8.450832	1.53931
22:30:00	470	595.6278	8.375131	1.78194
22:40:00	484	563.9558	5.330384	1.10131
22:50:00	413	606.7447	12.91652	3.12748
23:00:00	363	534.8869	11.45913	3.15684
23:10:00	379	529.8712	10.05808	2.65384
23:20:00	314	603.0022	19.26681	6.13592
23:30:00	369	607.9601	16.59734	4.62321
23:40:00	316	617.0552	20.07035	6.35137

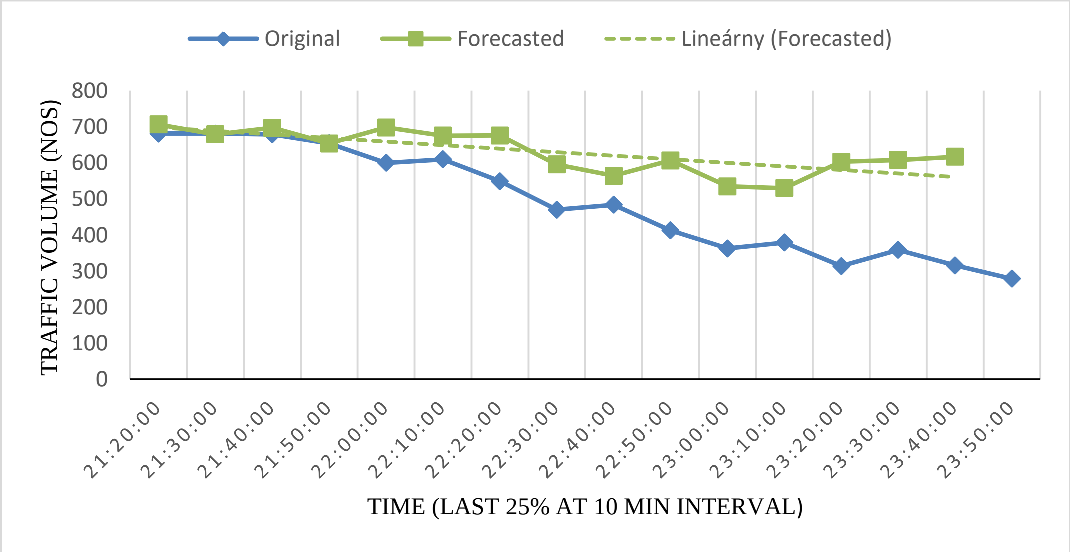


Fig4. *Original vs. forecasted graph using the ARIMA model.*

3.2 Monte Carlo simulation: Taking every 10 min traffic volume of 3 days as input Monte Carlo simulation process has been applied and simulated 14400 results. Then the traffic flow of each 10 min interval is forecasted. In Table 4, the result is shown as 2 hour interval. But figure 05 shows the total forecasting of each 10 min interval.

Tab 4. *Traffic flow prediction using Monte Carlo simulation*

Time	Actual flow	Predicted flow	Error (%)
00:00:00	340	365.42	7.47
02:00:00	63	81.56	29.46
04:00:00	211	186.87	11.43
06:00:00	664	638.99	3.76
08:00:00	1782	1709.52	2.63

10:00:00	1335	1359.37	1.82
12:00:00	1127	1217.18	8.00
14:00:00	1284	1301.52	1.36
16:00:00	1623	1585.80	2.29
18:00:00	1646	1686.42	2.45
20:00:00	946	969.20	2.45
22:00:00	682	635.48	6.82
Mean Average Percentage Error =			6.66

From the analysis the Mean Average Percentage Error has been found as 6.66% which is highly acceptable. In the region where the original data change abruptly (marked in the red box) there Monte Carlo simulation forecasts more perfectly than ARIMA model (Fig.4).

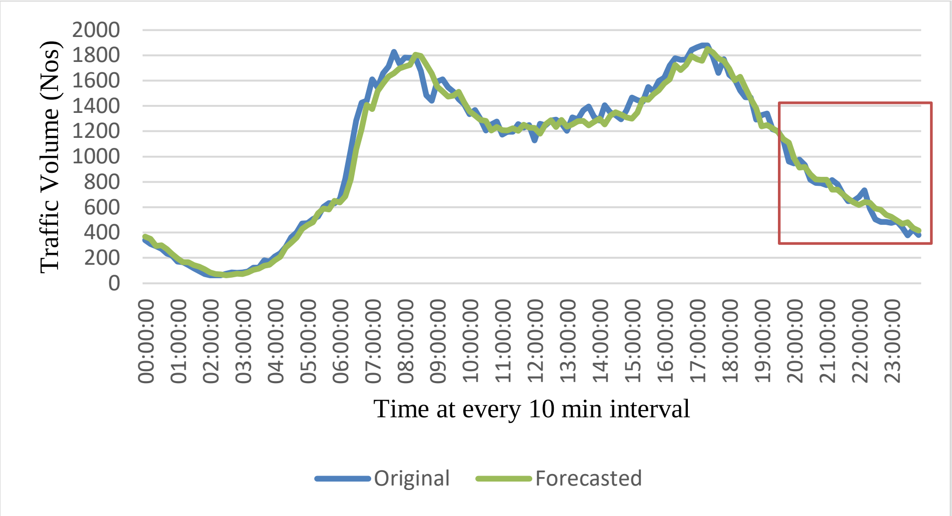


Fig5. *Original vs Forecasted traffic flow at every 10 min interval*

3 CONCLUSION

The data is semi-seasonal and non-stationary. Operating 1st difference makes the data stationary and partially meets the requirements of fitting Autoregressive Integrated Moving Average model. The results show that the forecasting of traffic volume using time series ARIMA model is nearly the same as the original volume. The residuals prove that it can be implemented in the practical field. But as the data has some seasonality and ARIMA method is for non-seasonal data sets that's why a little regression occurs here which can be understood from the forecast of 22:00:00 to 23:40:00. Adding with that time series can't forecast abnormal change in data points whereas there is a steep gradient contained in 23:10:00 to 23:40:00 of original data. This deviation results in a steeper change in that prediction region. In the mean time, the Monte Carlo simulation has overcome this region. It gives all the possibilities of that region particularly. It has shown only 6.66% Mean Absolute Percentage Error. So, in the case of short term prediction of semi-seasonal, non-stationary data, Time Series ARIMA model can be a good choice but the abrupt change zone can be overcome through Monte Carlo simulation.

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