Queue Length Prediction at Un-Signalized Intersections with Heterogeneous Traffic Conditions

Ishantha Rathnayake, Niranga Amarasinghe,
Faculty of Engineering, Sri Lanka Information Technology
New Kandy Road, Malabe, Sri Lanka.
ishantharathnayake95@gmail.com, niranga.a@sliit.lk

Vasantha Wickramasinghe
Faculty of Engineering, University of Peradeniya
Peradeniya, Sri Lanka.
vskw@eng.pdn.ac.lk

Kavindi Liyanage
Faculty of Humanities and Science, Sri Lanka Information Technology
New Kandy Road, Malabe, Sri Lanka.
kavindi.l@sliit.lk

ABSTRACT

Increasing queue lengths while reducing average vehicle speeds is a notable criterion in intersections with heterogeneous traffic conditions. Such queue lengths vary with different intersection controls. This study aimed to estimate the queue length at un-signalized intersections with heterogeneous traffic conditions. The study was done for un-signalized intersections in Peradeniya and Weliwita, Sri Lanka and the data were collected through video recordings. The queue lengths in an un-signalized intersection with mixed traffic conditions have an instantaneous aggressive variation due to the uncontrolled movements. Thus, a time series analysis with the aid of Vector Auto Regression (VAR) model was used in order to estimate the queue length. Variables considered in this study were arrival flow rate, discharge flow rate, number of conflicts for 15 seconds time intervals as independent variables and queue length at the end of each 15 seconds as the dependent variable. For the modelling, the procedure of "Box-Jenkins" method was followed. After the confirmation of the variables are stationary, Cointegration check and Granger causality tests were done to check the cointegration between variables and the granger causality between variables. Then, VAR models were developed using 80% data from the total data set for both locations. The remaining 20% of the data set was used to validate the model using the MAE, MAPE, and RMSE error values between the actual and predicted queues. Among both models, 0.94 of higher R^2 value and Durbin Watson value as 2 was obtained for the developed model using raw variables for Weliwita junction. Furthermore, the observed MAE, MAPE, and RMSE values for Weliwita model were 3,5 and 6%, respectively. Thus, the results of this study can be used to reduce traffic congestion while enhancing the safety of the users at un-signalized intersections in Sri Lanka.

KEYWORDS: *heterogeneous traffic, queue length, time series analysis, un-signalized intersections.*

1 INTRODUCTION

Increasing traffic congestion during peak hours has become a major problem in developing countries like Sri Lanka. This traffic congestion has led to increase potential parameters such as queue length, vehicle delay, travel time while decreasing the travel speed (Anusha et al., 2013). Intersections within the cities are congested frequently during peak hours (Vajeeran and Silva, 2019). Thereby, the excessive road traffic congestions result in reduced average vehicle speed while increasing the vehicle queue lengths at intersections in urban areas.

ISSN 2961-5011 | https://doi.org/10.54389/PKFL8922

Intersections can be classified into two categories. Signalized intersections and un-signalized intersections are the two types of intersections. The heterogeneous traffic condition at the signalized intersection can be controlled but at the un-signalized intersections, the traffic cannot be controlled. It's upon the driver's behavior. In the present scenario of ever-growing traffic congestion at the intersections, increasing the use of road transportation has led to reduce the vehicle speed, this arises the need of a queue prediction model to predict queue length at intersections (Anusha et al., 2013). Thereby, queue length can be recognized as an essential factor to measure the performance of both signalized and un-signalized intersections (Comret, 2016). This study was aimed to predict the queue length at un-signalized intersections while identifying the governing parameters that cause to queue lengths and to develop a time series model to predict the queue length at un-signalized intersections.

As per the authors' knowledge, no research has been conducted based on queue length prediction at un-signalized intersections with the aid of time series analysis but there is research that has been conducted for the queue length prediction at signalized intersection using the other methods. Those are tabulated in Table 1.

Table 1. Queue length predictions and the theories used in previous studies.

Country and the study	**Theory**	**Type of intersection**	**Condition of traffic**
China (Li et al., 2018)	LWR shockwave theory	Signalized intersection	Heterogeneous traffic condition
India (Parmar et al., 2020)	Multi Linear Regression Analysis	Signalized intersection	Heterogeneous traffic condition
USA (Comret., 2016)	Poisson model with analytical expressions	Signalized intersection	Heterogeneous traffic condition
China (Gao et al.,2020)	Shockwave theory	Signalized intersection	Heterogeneous traffic condition
Canada (Khan and Ali, 2010)	Shockwave theory	Signalized intersection	Heterogeneous traffic condition
USA (Anusha et al., 2013)	Queue polygon method	Signalized intersection	Heterogeneous traffic condition
Sri Lanka (Vajeeran and Silva., 2019)	Trial-and-error process using VISSIM simulation	Signalized and un-signalized intersections	Heterogeneous traffic condition
Germany (Heidemann and Wegmann.,1997)	Renewal queueing theory	Un-signalized intersections	Heterogeneous traffic condition

The previous studies demonstrate that the considered parameters have a significant influence in predicting queue lengths. Li et al., (2018) used vehicle arrival, discharge and turning movement while Ma et al., (2012) used stopping time, lagging time while Parmar et al., (2020) used lane width, flow, red time, and composition as the governing parameters for the study. Further, the studies have implemented various approaches for data collection to develop queue prediction models. Comret (2016) used mobile sensors, Li et al., (2017) used magnetic sensors while Gao et al., (2020) and Parmar et al., (2020) used video recordings to collect data. Li et al., (2018) and Anusha et al., (2013) have used 5 seconds and 10 seconds time sequences to extract the data.

However, from the literature survey it was clarified that only a small number of studies has been done previously based on un-signalized intersections. As per the authors' knowledge, only one study has been conducted for un-signalized intersections (Heidemann and Wegmann,1997). In that study, a mathematical model was developed with the aid of queueing theory to predict queue length. The rest of the studies were for queue length predictions at signalized intersections. Thereby the less amount of studies based on the queue prediction at un-signalized intersections was identified and further identified that there are no queue prediction models with respect to time which means no time series analysis has been done to predict the queue length. Thus, the study is focused on identifying the governing parameters and developing a time series analysis to estimate vehicle queue length at un-signalized intersections.

2 METHODOLOGY

The methodology of this study consisted of seven stages. Those are setting up the objectives, location selection, data collection, data extraction, data analysis, time series model development and validation of the model with the existing conditions.

2.1 Location selection

Locations were selected considering the developing queue and the availability of collecting data without any disturbances. Thereby the selected locations resided with optimum queue length and other governing parameters with heterogeneous traffic conditions. Figure 1 and Figure 2 show the selected location 1 which was the Peradeniya junction while Figure 3 and Figure 4 show the selected location 2 which was the Weliwita junction in Sri Lanka. Even though the selected road sections were single carriageways the observed width of the lanes were different. The type of the intersection was identified as a “T junction” with location 1 being an intersection of major- major approaches and location 2 being an intersection of major-minor approaches.

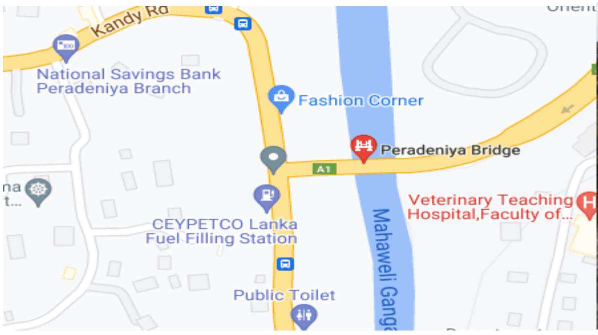

Figure 1. Trained image of selected Location 1

Figure 2. Generated queue sample from collected data Location 1

Figure 3. Trained image of selected Location 2

Figure 4. Generated queue sample from collected data Location 2

2.2 Data collection

From a field visit, it was observed that the development of the queue is varying from zero to 100m range for both locations. Thereby, the data collection was done with the aid of two cameras to cover the entire queue developing section. One camera was placed at downstream, and another camera was placed at upstream. Queue development at the selected approach at location 1 was recorded for two days. For location 1, a data collection was carried out on 16th April 2021 for a peak hour, starting from 12:30 p.m. till 1:30 p.m. and another data collection was carried out on 20th April 2021 for half an hour off-peak time, starting from 9:30 a.m. to 10:00 a.m. Similarly, another data collection was carried out on 30th July 2021 for location 2, starting from an off-peak hour 3:30 p.m. till a peak hour 5:30 p.m.

2.3 Data extraction

Data extraction was carried out manually by replaying the video multiple times. To measure the developed queue length a software called “TRACKER-4.11.0” was used (Tracker, 2021). Different vehicle categories were identified because of the heterogeneous traffic condition. Thereby, those were converted into one category using the Passenger Car Unit values (PCU). The PCU factors were obtained from Kumarage (1996) that study was done to find PCU standards for Highways in Sri Lanka . Those PCU factors are tabulated in Table 2.

Table 2. PCU factors (Kumarage, 1996)

Vehicle category	PCU factor
Motor Bike	0.5
Three-Wheeler	0.67
Car/Van/ Jeep	1
Medium Goods Vehicle (MGV)	1.75
Bus/Heavy Good Vehicle (HGV)	2.25

2.4 Model developing

Data were analyzed with respect to time. Therefore, a time series model was developed with the aid of the "EViews" student version software (Eviews 12 University Edition, 2021) to predict queue length at un-signalized intersections. The procedure of Box-Jenkins (1976) which has been used to predict the short-term traffic volume in Amman, Jordan's capital by Hamed et al (1995) was followed for this study. The analysis was conducted in seven main phases. Those were stationarity checking, optimal lag selection, cointegration checking, granger causality checking, model developing, stability and model fitting checking.

Considered independent variables for this study were arrival flow rate (PCUs per 15 seconds), discharge flow rate (PCUs per 15 seconds) and the number of conflicts (PCUs per 15 seconds) and as the dependent variable, queue length (meters) at the end of each 15 seconds time sequences.

2.4.1 Stationary checking

According to Box and Jenkins (1976), the stationarity check was carried out in two perspectives ways. Those were visual inspections of the results through the correlogram test and the unit root test.

I. Visual inspection through correlogram

The stationary condition of the selected variables was visually inspected to identify any trend or seasonal pattern with the aid of the graphical representations of the autocorrelation function (ACF) and partial autocorrelation function (PACF) on the correlogram test.

II. Unit root check

The unit root test was done under the Augmented Dickey Fuller (ADF) test. The test was conducted in two phases, with the first phase focusing just on the intercept and the second phase focusing on both the intercept and the trend. The probability values were checked to be less than 0.05 while obtaining t-statics values less than 5% to be the condition of stationary for variables and it was identified that the probability values of selected variables for the study were less than 0.05. Thus, it was confirmed that variables were stationary.

2.4.2 Optimal lag selection

For both locations lag value was selected from Akaike Information Criteria (AIC), which gives minimum error value among other criteria while providing the best results (Akaike., 1974). It was observed that lag 1 (time lag by one-time sequence which is 15s-time sequence, AIC= 9.031) and lag 3 (time lag by three-time sequences which is 45s-time sequence, AIC= 10.438) as the minimum error values for location 1 and location 2 respectively.

2.4.3 Johannes-cointegration test

Johansen cointegration test was used to examine the cointegration between the group of non-stationary series. The test results manifest that all the probability values were less than 0.05 which means that there is cointegration between variables. The considered hypothesis of the test is shown below,

H_0 – No cointegration between variables

H_1 – There is cointegration between variables

2.4.4 Granger causality test

By following (Granger, 1969), the test was done to check whether the independent variables cause dependent variables. The considered hypothesis of the test is shown below,

H_0 – Independent variables does not granger cause to dependent variables

H_1 – Independent variables granger cause to dependent variable

2.4.5 Model developing

After identifying that the variables are stationary, cointegration between variables does not exist and the independent variables granger cause to dependent variable, Vector Autoregression (VAR) model was developed with the aid of the “EViews” software.

2.4.6 Stability and model fitting checking

I. Stability checking

To check the stability AR roots test was carried out for both models. The conditions of the test are as follows,

- If points lie inside the circle, the model satisfies the stability condition.
- If points lie outside the circle, the model un-satisfies the stability condition.

II. Check Model fitting

Forecasting graphs were observed to check the model fittings for the developed models. The Conditions of the test are as follows,

- If the Theil inequality coefficient is 0 or close to 0, the model is well fitted
- If the Theil inequality coefficient is 1 or close to 1, the model is not fitted

3 RESULTS AND DISCUSSION

To develop the model, 80% of data from the total set of data were used and the remaining 20% of the data were used to validate the models.

3.1 Developed VAR models

I. Developed VAR model for Peradeniya junction (Location 1)

Considering the queue length as the dependent variable and arrival flow rate, discharge flow rate and the number of conflicts as the independent variables a VAR model was developed. The selected lag for the model was lag 1 which was observed from the optimal lag selection test under AIC criteria.

Table 3 manifest the developed VAR model along with the individual significance of each selected variable for location 1. Thus, the queue length prediction model with coefficients that are related to each variable is shown below in Equation (1) and the observed probability values of the coefficients are less than 0.05 and significant.

$$\begin{aligned} Queue\ length \ = \ & (0.949357 \times Queue\ length_{t-1}) + (-34.1800 \times Arrival\ rate_{t-1}) \\ & + (31.77035 \times Discharge\ rate_{t-1}) \\ & + (-0.889981 \times Number\ of\ conflicts_{t-1}) + 9.412055 \end{aligned} \tag{1}$$

Where;

(t – 1) ; time lag by one time sequence. For this study 15s-time sequence.

Table 3. Developed VAR model for location 1 (Peradeniya model)

VAR model				
Related variable	**Coefficient number**	**Coefficient value**	**T - Statistic**	**Probability value**
Queue length	**C(1)**	0.949357	15.97094	0.0000
Arrival rate	**C(2)**	-34.18000	-8.668305	0.0000
Discharge rate	**C(3)**	31.77035	8.400800	0.0000
Number of conflicts	**C(4)**	-0.889981	-2.527398	0.0118
Model constant	**C(5)**	9.412055	2.935011	0.0035
$Queue\ length = (C[1] \times Queue\ length_{t-1}) + (C[2] \times Arrival\ rate_{t-1}) + (C[3] \times Discharge\ rate_{t-1}) + (C[4] \times Number\ of\ conflicts_{t-1}) + C[5]$				
R-Squared	0.798569	**Durbin-Watson**	1.811990	

II. Developed model for Weliwita junction (Location 2)

Considering the queue length as the dependent variable and arrival flow rate, discharge flow rate and the number of conflicts as the independent variables a VAR model was developed. The selected lag for the model was lag 3 (45 second lag) which was observed from the optimal lag selection test under AIC criteria.

Table 4. Developed VAR model for location 2 (Weliwita model)

VAR model				
Related variable	**Coefficient number**	**Coefficient value**	**T - Statistic**	**Probability value**
Queue length	**C(1)**	0.863241	16.08351	0.0000
Queue length	**C(2)**	0.101790	1.440552	0.1499
Queue length	**C(3)**	-0.043469	-0.819963	0.4124
Arrival rate	**C(4)**	-32.97608	-33.58264	0.0000
Arrival rate	**C(5)**	-2.982159	-1.485449	0.1376
Arrival rate	**C(6)**	0.539431	0.266165	0.7901
Discharge rate	**C(7)**	26.81571	38.18857	0.0000
Discharge rate	**C(8)**	1.843290	1.153714	0.2488
Discharge rate	**C(9)**	-0.815272	-0.510864	0.6095
Number of conflicts	**C(10)**	-1.817695	-8.132326	0.0000
Number of conflicts	**C(11)**	0.026664	0.110768	0.9118
Number of conflicts	**C(12)**	0.255436	1.062748	0.2881
Model constant	**C(13)**	10.93986	7.551259	0.0000
$Queue\ length = (C[1] \times Queue\ length_{t-1}) + (C[2] \times Queue\ length_{t-2}) + (C[3] \times Queue\ length_{t-3}) + (C[4] \times Arrival\ rate_{t-1}) + (C[5] \times Arrival\ rate_{t-2}) + (C[6] \times Arrival\ rate_{t-3}) + (C[7] \times Discharge\ rate_{t-1}) + (C[8] \times Discharge\ rate_{t-2}) + (C[9] \times Discharge\ rate_{t-3}) + (C[10] \times Number\ of\ conflicts_{t-1}) + (C[11] \times Number\ of\ conflicts_{t-2}) + (C[12] \times Number\ of\ conflicts_{t-3}) + C[13]$				
R-Squared	0.945790	**Durbin-Watson**	2.000140	

Table 4.2 manifest the developed VAR model along with the individual significance of each selected variable for location 2. Even though some of the coefficients were not significant (Probability values more than 0.05) by means the variables do not singly help to predict the dependent variable, but the coefficients were jointly helping to predict the queue length (Dependent variable) and it was identified from the Wald test under coefficient diagnostic test. The test was done by making a null

hypothesis, which is C (2) = C(3) = 0 (Davison and Mackinnon, 1993), and if the probability values are less than 0.05, we reject the null hypothesis. The observed probability values for this model were less than 0.05. Thereby the null hypothesis was rejected and the alternative hypothesis which is C(2) = C(3) ≠ 0 was accepted, thereby the coefficients are jointly helping to predict the dependent variable.

Thus, the queue length prediction model with coefficients that are related to each variable is shown below in Equation 2,

$$\begin{aligned} Queue\ length &= (0.863241 \times Queue\ length_{t-1}) \\ &+ (0.101790 \times Queue\ length_{t-2}) \\ &+ (-0.043469 \times Queue\ length_{t-3}) \\ &+ (-32.97608 \times\ Arrival\ rate_{t-1}) \\ &+ (-2.982159 \times Arrival\ rate_{t-2}) \\ &+ (0.539431 \times Arrival\ rate_{t-3}) \\ &+ (26.81571 \times Discharge\ rate_{t-1}) \\ &+ (1.843290 \times Discharge\ rate_{t-2}) \\ &+ (-0.815272 \times Discharge\ rate_{t-3}) \\ &+ (-1.817695 \times Number\ of\ conflicts_{t-1}) \\ &+ (0.026664 \times Number\ of\ conflicts_{t-2}) \\ &+ (0.255436 \times Number\ of\ conflicts_{t-3}) + 10.93986 \end{aligned} \tag{2}$$

where;

(t – 1) ; time lag by one-time sequence. For this study 15s-time sequence,
(t – 2) ; time lag by two-time sequence. For this study 30s-time sequence, and
(t – 3) ; time lag by three-time sequence. For this study 45s-time sequence.

3.2 Validation of developed two models

To validate the model, the stability of the developed model was obtained while checking the model fitting with the aid of the Theil inequality coefficients under forecasting graphs and a further residual correlation test was done.

I. Model Stability Check

Figure 5 and Figure 6 manifest the results AR Root test. Results indicate that no points lie outside of the circle for both models. Thus, both models are in stable condition.

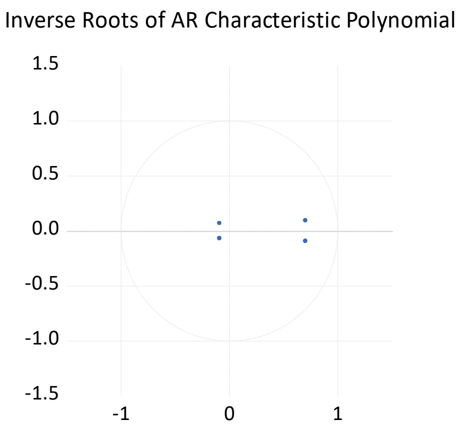

Figure 5. AR Roots test results for Peradeniya model

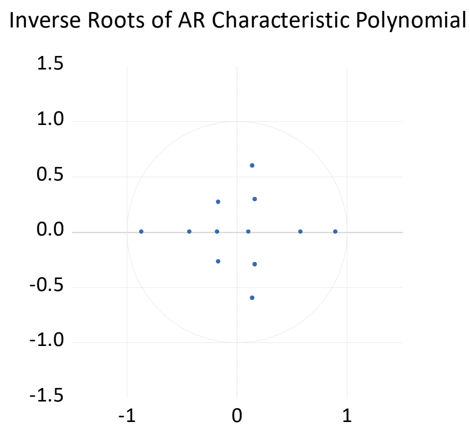

Figure 6. AR Roots test results for Weliwita model

II. Residual correlation test

Residual correlation test was done to check whether there is any correlation between variables under the selected lag. The considered hypothesis of the test is shown below,

H_0 – No correlation between variables
H_1 – There is a correlation between variables

Table 5 indicates the results of residual correlation test results to both models. Table 5 further manifest that there is no correlation between variables for the selected lag.

Table 5. Residual correlation test results

Model	Selected lag (AIC criteria)	Probability value
Peradeniya model	1	0.0000 ($p < 0.05$)
Weliwita model	3	0.0403 ($p < 0.05$)

III. Model fitting check

Model fitting was observed with the aid of Theil inequality coefficient under forecasting graphs. The observed coefficients are tabulated in Table 6.

Table 6. Theil inequality coefficients for both models

Model	Theil inequality coefficient
Peradeniya model	0.118
Weliwita model	0.278

Theil inequality coefficients of both models are close to 0. This means both models are well fitted to the trained data set.

3.3 Discussion on results

After the validation and the confirmation of the stability of the developed models, the comparison of the actual queue and the predicted queue was done to check the error percentages with the developed models for the same location and other locations. To evaluate the accuracy of the proposed model, the Mean Average Error (MAE), Mean Average Percentage Error (MAPE), and Root Mean Square Error (RMSE) values were calculated using the equations (3), (4), (5) respectively. (Li et al., 2018).

$$MAE = \frac{1}{m}\sum_{m}|Observation - Prediction| \tag{3}$$

$$MAPE = \frac{1}{m}\sum_{m}\left|\frac{Observation - Prediction}{Observation}\right| \times 100\% \tag{4}$$

$$RMSE = \frac{1}{m}\sqrt{m\sum_{m}(Observation - Prediction)^2} \tag{5}$$

Here *m* denotes the number of time sequences.

Equation 3, 4 and 5 was used to calculate the error values between the actual queue and the predicted queue for the selected locations. Here the developed models were used to predict the queue at the same location as well as the other selected location. Thereby, the most accurate model was selected as the queue prediction model. Figure 7 manifests the comparison results between actual peak queue at Peradeniya vs the predicted queue using the Peradeniya model and Weliwita model.

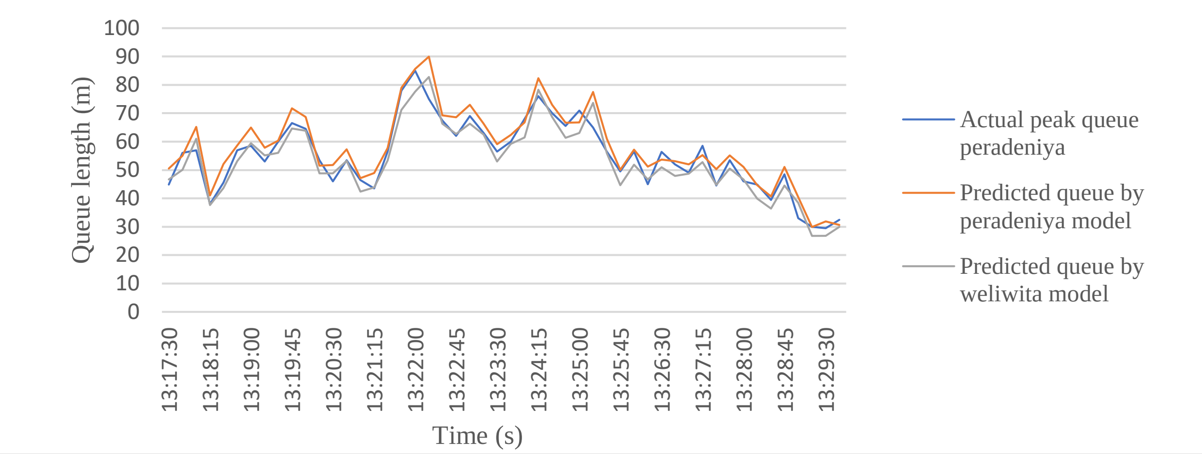

Figure 7. Actual peak queue at Peradeniya vs Predicted queue by both models

During the field data collection stage, it was observed that the Peradeniya junction has a continuous arrival rate while developing longer queues consistently. Thus, zero queues were not identified through the data collection period. Using the equations of 3, 4, 5 MAE, MAPE and RMSE values were calculated for the developed models and tabulated in Table 7.

Table 7. Calculated MAE, MAPE and RMSE values for both models

Actual queue at Peradeniya	Predicted queue by Peradeniya model	Predicted queue by Weliwita model
MAE	3.713	3.305
MAPE	6.699 %	6.070 %
RMSE	4.755	3.999

Hence the results of Table 7 revealed fewer error values, both models can be used to predict the peak queue at Peradeniya junction. But it was further identified that using the Weliwita model to predict the peak queue at Peradeniya gives lesser MAE, MAPE and RMSE values than the Peradeniya model.

Figure 8 manifest the comparison results between actual peak queue at the Peradeniya vs the predicted queue using the Peradeniya model and Weliwita model.

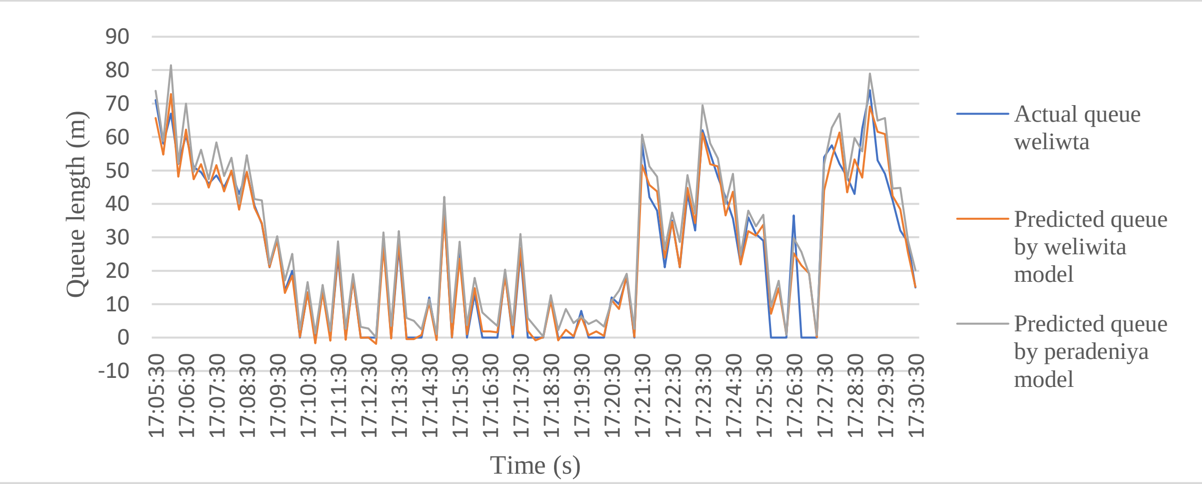

Figure 8. Actual peak queue at Weliwita vs Predicted queue by both models

During the field data collection stage, it was identified that the Weliwita junction condition was different from the Peradeniya junction. The observed arrival rate was not continuous. Thereby, zero queues were identified on that location. But from the graphical representations of Figure 8, it can be identified that both models predict the queue well. It was further identified that the accuracy of the zero-queue prediction of the Peradeniya model is lower than the Weliwita model. Thus, to obtain the accurate model equations 3, 4, 5 were used and the results are tabulated in Table 8.

Table 8. Calculated MAE, MAPE and RMSE values for both models

Actual queue at Weliwita	Predicted queue by Peradeniya model	Predicted queue by Weliwita model
MAE	5.043	3.042
MAPE	9.968%	5.665%
RMSE	6.800	5.042

Table 8 manifest that the obtained MAE, MAPE and RMSE values of the Peradeniya model are much higher than the Weliwita model when predicting the peak queue at the Weliwita junction. However, the results of all the comparisons indicate that the Weliwita model gives much accurate and good results. The only difference that identified was the less accuracy of zero queue prediction of the Peradeniya model.

Thus, for the confirmation of zero queue prediction, another comparison was done using the off-peak hour data of Location 1 (Peradeniya junction) and Weliwita model to predict the queue and the results are presented in Figure 9.

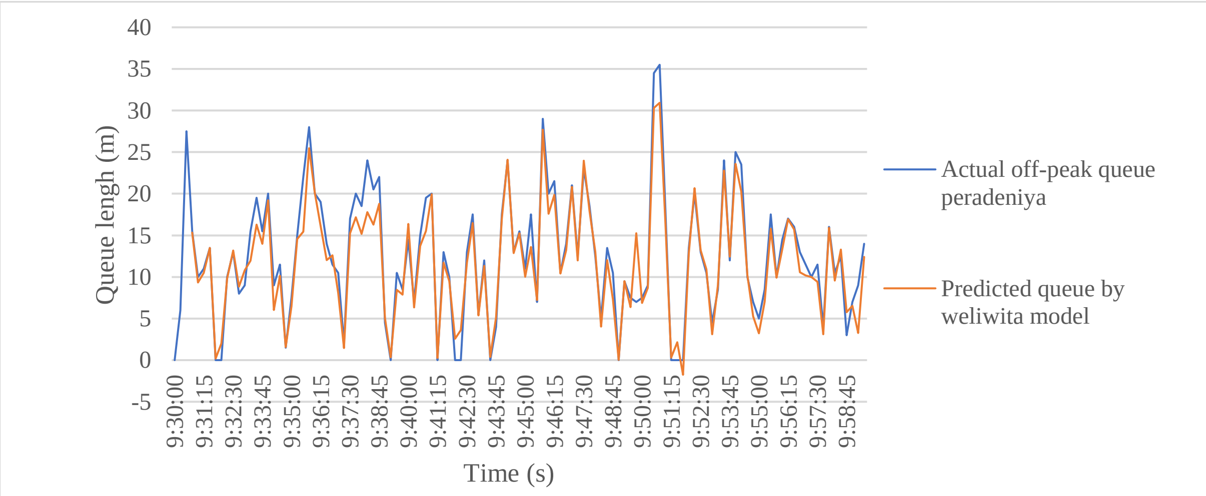

Figure 9. Actual off-peak queue vs Predicted queue by Weliwita model

The graphical representation shows that using the Weliwita model an accurately predicted queue can be obtained. It can be further observed that the accuracy of zero queue prediction is much higher in the Weliwita model.

Table 9. Calculated MAE, MAPE & RMSE values for Weliwita model

Actual off-peak queue (Peradeniya junction) vs predicted queue (By Weliwita model)	
MAE	1.457
MAPE	11.471%
RMSE	2.089

The results of each comparison revealed that the Weliwita model has lesser error values in queue length prediction for both locations while maintaining a higher R^2 value of 0.94%. Table 8 results manifest that the accuracy of zero-queue prediction using the Weliwita model was higher than the Peradeniya model. Thereby the queue prediction model which was developed for the Weliwita junction can be used to predict the queue length at any T type un-signalized intersection.

The MAE, MAPE and RMSE value comparison has been done between the developed model for Weliwita junction and the developed models for other locations in worldwide and tabulated in Table 10.

Table 10. Results comparison with developed queue prediction models

	Weliwita junction [Malabe, Sri Lanka]Developed model	China(Li et al., 2018)	USA(Anusha et al., 2013)
Intersection type (Signalized /Un-signalized)	**Un-signalized**	**Signalized**	**Signalized**
Method used	**Time series analysis**	**LWR shockwave theory**	**Queue polygon method**
MAE	3.042	1.83	-
MAPE	5.665%	11.28%	-
RMSE	5.042	2.42	1.3

MAE, RMSE and MAPE values equal to or lesser than 3, 3 and 20% which means the model is in the satisfactory range (Li et al., 2018). MAE, RMSE and MAPE values of the developed model are 3.042, 5.042 and 5.665%. Thus, the observed values for the Weliwita model are in the satisfactory range.

4 CONCLUSION

In this study, time series analysis with the aid of the Vector Auto Regression (VAR) model was used to develop a queue length prediction model in order to predict the developing queues at un-signalized intersections. The vehicle characteristics in a heterogeneous traffic condition, influencing the development of the vehicle queue length were identified and analyzed in this study. It was identified that the governing parameters which cause queue length development were arrival flow rate, discharge flow rate and the number of conflicts.

As full filling the secondary objective of this study, the study was adopted considering two highly congested locations in Sri Lanka. One model was developed for Peradeniya junction, Kandy and the other one was developed for Weliwita junction (located in front of SLIIT), Malabe. The assumptions made before developing the model, such as variables are stationary, the granger causality between variables, cointegration between variables was tested and confirmed using 80% data. After developing the model, validation and stability were checked using 20% data. The observed results manifest that the selected variables have a significance influence on developing queue length for both locations. Further, the observed MAE, MAPE and RMSE values for both models reveal that the Weliwita model has more prediction accuracy while maintaining a higher R^2 value and lesser error values for both locations. Thereby, the developed model for Weliwita junction can be implemented to predict the queue length at any T type un-signalized intersection with heterogeneous traffic conditions. This model can be used as an alternative way to predict the queue length when measuring queue length to signalize an un-signalized intersection.

This study was done only focusing on T type intersections where has single carriageways. Thereby, Further research can be done considering different type of intersections that has different geometrical parameters as well as considering more variables such as lane changing phenomena and pedestrian crossing.

ACKNOWLEDGEMENT

Authors would like to thank Shenura Jayatilleke for helping for data collection and R. G. R. M. L. Bandara & M. G. P. Kumari for their help to conduct research work. This research was supported by the Accelerating Higher Education Expansion and Development (AHEAD) Operation of the Ministry of Higher Education, Sri Lanka, funded by the World Bank.

REFERENCES

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716-723. https://doi.org/10.1109/tac.1974.1100705

Anusha, S. P., Lalitha Devi, V. and Anuj Sharma, 2013"A Simple Method for Estimation of Queue Length". *Civil Engineering Faculty Publications.* 48.

Box, George E. P. and Gwilym M. Jenkins (1976). *Time Series Analysis: Forecasting and Control*, Revised Edition, Oakland, CA: Holden-Day.

Comert, G. (2016). Queue length estimation from probe vehicles at isolated intersections: Estimators for primary parameters. *European Journal Of Operational Research*, *252*(2), 502-521. https://doi.org/10.1016/j.ejor.2016.01.040

Davison, R., & MacKinnon, J. (1993). "*Estimation and Inference in Econometrics*". Oxford: *Oxford University Press*.

EViews 12 University Edition. (2021). Retrieved 10 April 2021, from http://www.eviews.com/EViews12/EViews12Univ/evuniv12.html

Gao, K., Huang, S., Han, F., Li, S., Wu, W., & Du, R. (2020). An Integrated Algorithm for Intersection Queue Length Estimation Based on IoT in a Mixed Traffic Scenario. *Applied Sciences*, 10(6), p.2078. http://dx.doi.org/10.3390/app10062078

Granger, C. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, *37*(3), 424. https://doi.org/10.2307/1912791

Hamed, M., Al-Masaeid, H., & Said, Z. (1995). Short-Term Prediction of Traffic Volume in Urban Arterials. *Journal Of Transportation Engineering*, *121*(3), 249-254. https://doi.org/10.1061/(asce)0733-947x(1995)121:3(249)

Heidemann, D., & Wegmann, H. (1997). Queueing at unsignalized intersections. *Transportation Research Part B: Methodological*, *31*(3), 239-263. https://doi.org/10.1016/s0191-2615(96)00021-5

Kumarage, A. (1996). PCU Standards for Sri Lanka Highway Design. *Conference: Institution Of Engineers Sri Lanka Annual Sessionsat: Colombo*.

Khan, M. D. and Ali, S., "Real-time estimation of queue length at signalized intersections" (2010). *Electronic Theses and Dissertations*, 8230

Li, B., Cheng, W., & Li, L. (2021). Real-Time Prediction of Lane-Based Queue Lengths for Signalized Intersections. *Journal of Advanced Transportation*, 2018, pp.1-18. http://dx.doi.org/10.1155/2018/5020518

Li, H., Chen, N., Qin, L., Jia, L., & Rong, J. (2017). Queue length estimation at signalized intersections based on magnetic sensors by different layout strategies. *Transportation Research Procedia*, *25*, 1626-1644. https://doi.org/10.1016/j.trpro.2017.05.212

Ma, D., Wang, D., Bie, Y., Sun, F., & Jin, S. (2012). A Method for Queue Length Estimation in an Urban Street Network Based on Roll Time Occupancy Data. *Mathematical Problems In Engineering*, *2012*, 1-12. https://doi.org/10.1155/2012/892575

Parmar, D., Gore, N., Rathva, D., Dave, S., & Jain, M. (2019). Modelling Queuing of Vehicles at Signalized Intersection. *Transportation Research*, 557-565. https://doi.org/10.1007/978-981-32-9042-6_44

Tracker, Video Analysis and Modeling Tool for Physics Education. (2021). Retrieved 19 April 2021, from https://physlets.org/tracker/

Vajeeran, A., & Silva, G. (2020). Identification of Effective Intersection Control Strategies During Peak Hours. *Transportation Research Procedia*, *48*, 687-697. https://doi.org/10.1016/j.trpro.2020.08.069