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Original Article

Mathematical Modeling of Traffic Flow in Kampala City Using the Moving Observer Method

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ABSTRACT

The purpose of the study was to investigate the variables affecting traffic flow in Kampala Central Business District (CBD), employing a quantitative approach. The rapid urbanization has led to a huge increase in the number of vehicles, resulting in traffic congestions, delays, and financial losses especially in the Kampala CBD area. Data on traffic density, speeds, and driver behaviors were collected for a period of 20 days from five selected road sections leading into and out of the city which included traffic on Entebbe Road, Jinja road, Sir Apollo Kaggwa Road, Yusuf Lule and Wandegeya roads using the moving observer method. Regression analysis was done to identify the relationships between the variables, leading to the development of a predictive model for traffic flow. The study found out that the flow tends to increase as the day progresses and as well flow rate increases with increase in density. As the week progressed, the flow rate decreased as number of people coming to town on weekends is low since there is no work. A mathematical model was generated which could be used to predict the traffic intensity on the road at a given day and time. The model shows that changing from weekdays to weekend, the flow decreases by about 29%, and as density increases by 1%, the flow also increases by 1.5% over time. The study recommends prioritizing public transportation improvement, establishment of out of city parking yards, utilizing the other various means of transport other than road and promoting non-motorized modes of transportation in order to reduce traffic density on the road and subsequently manage congestion.

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INTRODUCTION

In developing nations, traffic levels in cities is rising alarmingly (Arnott, et al., 2005). Traffic congestion in urban areas poses significant challenges, resulting in economic losses and reduced quality of life for residents. Kampala, Uganda, is no exception, with the daily cost of congestion estimated at USD 1.5 million according to Baertsch (2020), highlighting the urgent need for effective traffic management strategies.

The guidelines for the compilation of traffic impact assessments from Kampala Capital City Authority (KCCA), shows attempts to model traffic in Uganda. These guidelines clearly highlight the negative effects of traffic, including fatalities and accidents, decreased profitability for companies as a result of longer travel times, and discouragement to investors and other stakeholders. While previous studies by Nansereko (2019) and Zanule (2015) have explored traffic congestion in Kampala, there remains a gap in appreciation of the impact of the variables influencing traffic flow that would help in understanding how they interact with each other to cause traffic congestion aiding prediction of traffic trends.

OBJECTIVES OF THE STUDY

The main objective was to model traffic flow on Kampala roads using the moving observer method

Specific Objectives

- To determine the traffic variables responsible for the amount of traffic in Kampala.
- To determine the relationship between the traffic variables throughout various times of the day for different days.
- To develop a predictive traffic flow model

Microscopic and Macroscopic traffic variables

Langer et al (2020) and Khan and Gulliver (2018), identified two types of traffic variables that influence its flow, these are macroscopic and microscopic characteristics. Microscopic traffic variables focus on how individual vehicles interact with one another considering the driver behavior, vehicle locations, and distance and time headways. Macroscopic traffic variables consider the whole traffic flow pattern and include parameters like flow, density and speed.

Abdulrahman et al (2017) pointed out the important macroscopic traffic flow variables as density, flow, travel time, and speed. According to Maerivoet and Bart (2005), drivers operating various cars, each with unique features, make up the flow of traffic on the road. Microscopic characteristics are determined by the behavior of each driver, as well as the physical characteristics of the vehicles. These characteristics include length, space and time headway.

Moving Car Observer Method of Data Collection

The moving observer method is a method that is widely used to estimate the average journey time and traffic flow. This technique involves a test vehicle performing a series of runs both "with" and "against" traffic (Solanki, et al., 2016).

The major advantage of the moving observer method is that flow and speed data may be gathered simultaneously. Additionally, it is cost-effective because measuring requires fewer participants and takes less time (Barua, et al., 2015). Other methods like remote sensing using drones or satelites require sophisticated software and are expensive (Ossen, 2008).

Guerrieri, et al. (2019) in their study used the moving observer method and noted that it requires

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a number of runs in a test vehicle driven both "with" and "against" a one-way traffic flow. For each run, the test vehicle observers record the following data:

- Cars the test vehicle passed, ii) The number of vehicles passing the test vehicle while it is moving, iii) The test vehicle's average speed and iv) The length of the run and the test vehicles travel times on each run.

METHODS AND MATERIALS

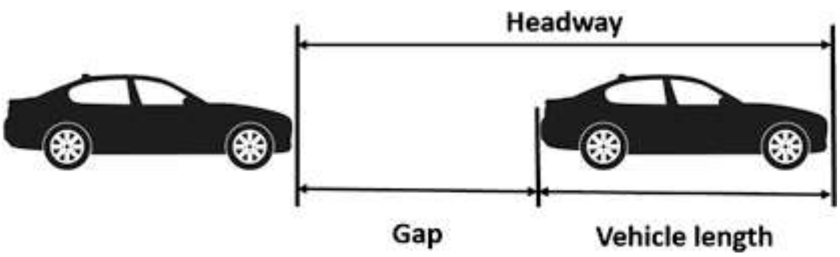
The study utilized the moving observer method to collect data on traffic parameters such as density, flow, headways and speed along selected road sections leading into and out of Kampala CBD. Data collection involved recording vehicle counts, travel times, speeds, distances, allowing for the calculation of microscopic and macroscopic traffic variables. Regression analysis was then employed to identify the relationships between variables and develop predictive model for traffic flow.

Data collection

The study used the moving observer method technique since it measures all the variables at once and was cheap to deploy. Permission to carry out the study was sought from the Traffic Department of Uganda Police. One-month period was granted for this study. Data collection started daily from 6.30 am through to 6:30 pm for a cumulative period of one month.

Three field data collection assistants manned each section of the selected road stretches. One assistant moved at a constant speed which was recorded by the observer. While moving in the same direction as the vehicles on the road, the observer recorded the number of vehicles overtaking and those overtaken by the observer moving on the pavement side of the road. The microscopic traffic variables were recorded by ascertaining the number of vehicles in a given stretch at a given time. A stopwatch timer and a record sheet were used to capture the information. Two arbitrary marks were set on the road sections at a distance sufficient enough for the moving observer to capture various vehicles within the selected stretch. The time headway was obtained by determining the time the vehicle took to cross the two reference points while space headway was determined using the number of vehicles within the specified length as shown in figure 1.

Figure 1: Headways Demonstration



Source: Google

Images

After the data was collected, the other variables were calculated as follows:

a) Traffic density (k) was calculated according to Saurav, et al. (2015) as,

$$\boldsymbol{k = \frac{q}{v_s}} \quad \text{................} \quad \textbf{Equation 1}$$

Where q is the flow (intensity), k being density and v_s being speed.

b) Then the other unknowns were calculated as density q using the formula noted in Wright (1973)**,**

$$\boldsymbol{q = \frac{m_\omega + m_a}{t_\omega + t_a}} \quad \text{..........} \quad \textbf{Equation 2}$$

Where $\boldsymbol{m_\omega}$-number of vehicles moving with, $\boldsymbol{m_a}$-number of vehicles moving against traffic

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Tw-time taken while moving observer is moving along with traffic. *Ta*-time moving against

c) Speed, Vs, unknown was also calculated using the formula highlighted in Abdulrahman, et al. (2017),

$$v_s = \frac{l}{t_\omega - \frac{m_\omega}{q}}$$

……………………………………...Equation 3

Where *l* is length of stretch.

Data analysis

The collected data were organized, cleaned, graphed and analyzed using Microsoft Excel as percentages and mean. Using multiple linear regression, the relationship between the variables was established.

Model development

Using multiple linear regression, the relationship between the variables of speed, density, flow and headways was established. As well, a model that predicts traffic magnitude was developed. The general model was generated as shown in Equation 4.

$$y = c + \alpha x_1 + \beta x_2 + \gamma x_3 + \theta x_4 \text{………………} \textbf{Equation 4}$$

where: y – flow, x_1 -time, x_2- density (vehicle/km), x_3- day, x_4- road stretch, c-intercept;

,$\alpha, \beta, \gamma, \theta$ -coefficients

The coefficients were obtained using Microsoft excel multiple linear regression and interpreted in relation to the magnitude and direction of effect on the dependent variable to draw relationships and patterns.

Model testing

The data collected were divided into two phases; phase one for Three road stretches (Jinja Road, Entebbe Road, Yusuf Lule Road) and phase two for the other two roads (Sir Apollo Kagwa Road, and Wandegeya road), data from the first phase was used to develop the model and data from phase 2 was used to test the model. The observed data from the field and predicted data using the model were compared and their relationship was determined using the Chi-square goodness of fit method

Reliability and Validity

The vehicle counts were carried out for over many time intervals to increase the confidence to 95%. Every 15-minute interval, a count would be carried out to give more accuracy to the counts. 48 data points were collected on each road daily. Scatter plots were used to compare data to see the patterns and if there are relationships with the data collected. The data obtained from the field was compared with the predicted flow by the model and graphs plotted to determine the relationships.

RESULTS

Table 1 shows sample data from one of the road sections.

Table 1: Sample Data from Field

Time	No. Veh. Passed (Mo)	No. Veh Passing (Mp)	Time With (Tw) Secs	(Ma)	Time (Ta) Secs	Mw =Mp-Mo	Flow Q=(Mw+ Ma)/(Tw+ Ta)	Speed V (Km/Hr)	Density K=Q/V (Veh/Km)
6.30	0	5	113			5	172.2	63.87096774	2.695652174
6.45				6	117	0			
7.00	0	5	113			5	183.1	36.81818182	4.971751412
7.15				7	123	0			
7.30	0	3	119			3	134.4	13.96551724	9.626556017
7.45				6	122	0			
8.00	0	7	115			7	186.2	26.55737705	7.011494253
8.15				5	117	0			
8.30	0	5	115			5	105.0	9.569620253	10.97222222

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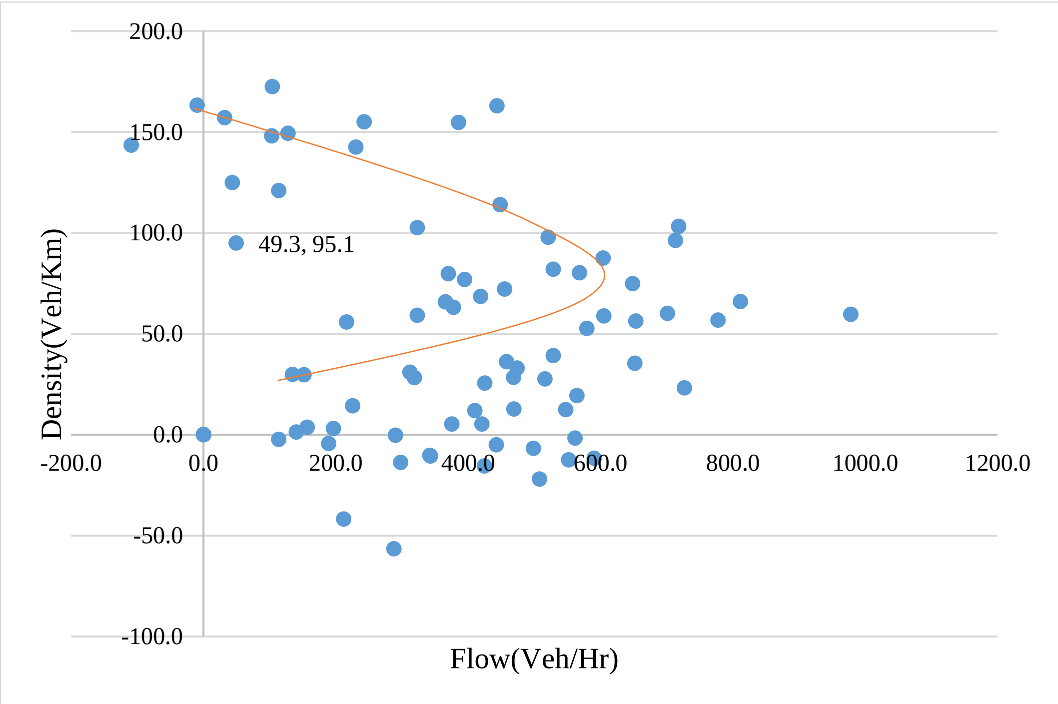
8.45				2	125	0			
9.00	0	4	115			4	209.1	11.70278638	17.86998617
9.15				10	126	0			
9.30	0	10	117			10	270.0	33.06122449	8.166666667
9.45				8	123	0			
10.00	0	11	114			11	288.6	23.26530612	12.40506329

The collected data are used to calculate the other variables which are required in the study including density, speed, flow, headways. Graphs are plotted showing the relationship between the variables and the data are grouped together for further analysis with regression using excel.

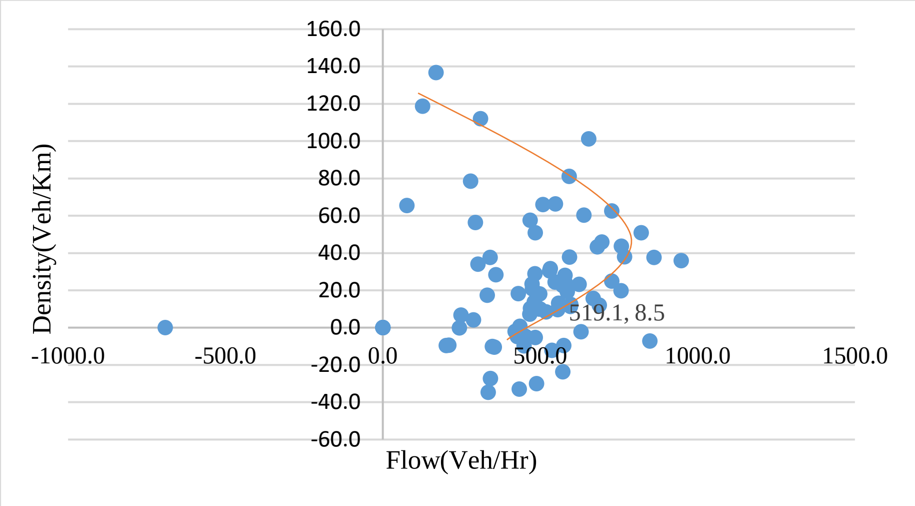
Figure 2 shows that initially, traffic flow increases with density, but beyond a certain threshold, further increases in density led to decreased flow, indicating congestion.

Figure 2: Density Flow Relationship at one of the Road Sections



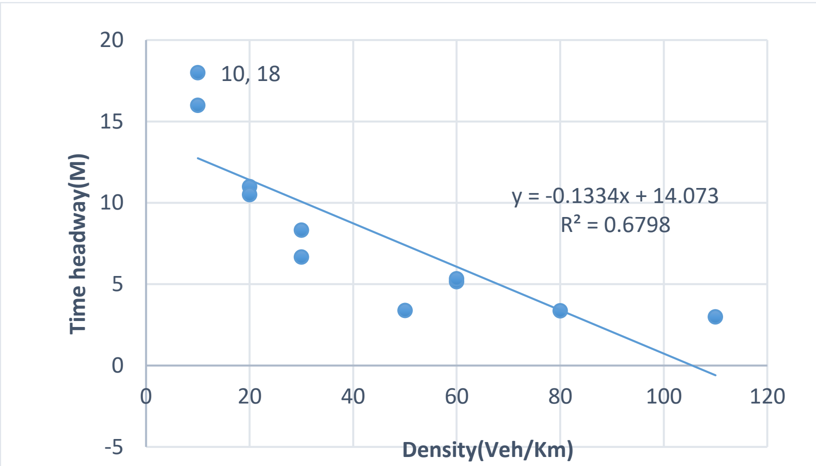
During periods of lower traffic density, vehicles were able to move more freely, resulting in a higher flow rate. The flow rose along with the density. This showed that originally, the flow of vehicles grew as more cars entered the route and the amount of traffic rose then the flow later started to reduce as shown in Figure 3. This relationship suggested that higher traffic density-imposed congestion that hindered the smooth flow of vehicles, resulting in slower speeds. The increase in density led to a higher number of vehicles sharing the same road space, which resulted in reduced gaps between vehicles, frequent braking, and overall slower movement.

Figure 3: Density Flow Relationship at another Road Section



Microscopic variables such as space and time headways also influence traffic flow, showing a negative slope linear relationship, with denser traffic resulting in reduced headways and increased congestion as shown in the Figure 4.

Figure 4: Time Headway and Density Relationship



Model Formulation

The study used multiple linear regression (Equation 4 above) using the calculated variables from Table 1 to forecast future trends of the traffic along the roads and obtained the coefficients of the model as shown in Table 2.

Table 2: Regression statistics

Multiple R	0.762670715		
R Square	0.581666619		
Adjusted R Square	0.58088977		
Standard Error	96.57009107		
Observations	2159		
ANOVA			
	Df	*SS*	*MS*
Regression	4	27930750.27	6982687.567
Residual	2154	20087735.48	9325.782489
Total	**2158**	**48018485.75**	

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	Coefficients	***Standard Error***	***t Stat***
Intercept	259.2500131	10.3494597	25.04961811
X Variable 1	-0.106714561	0.324670668	-0.328685563
X Variable 2	1.509994982	0.058465344	25.82718044
X Variable 3	-29.69826519	1.262568418	-23.52210364
X Variable 4	-0.025874282	1.476741849	-0.017521195

$$\boldsymbol{y = 259.250 - 0.107x_1 + 1.510x_2 - 29.698x_3 - 0.026x_4} \text{..... Equation 5}$$

y – flow, x_1 -Time, x_2- Density, x_3- Day, x_4- Road stretch

The large negative value on variable 3 shows lower traffic as weekends approach, positive variable 2 shows a positive relationship between traffic density and flow as they increase together which reflects higher flow rate in dense traffic while a small negative value on variable 4 shows different road sections having a slight impact on the flow.

The coefficients in Table 1 helped generate Equation 5. Using equation 5, predicted values of flow were generated to be compared with the observed flow values from the field.

Model Validation

Data from the field was subjected to regression analysis in order to see how much the selected variables were able to explain the traffic flow pattern in Kampala city and the findings were as shown in Table 2. The R-square value was 0.582. This showed that 58.2% of the variability in traffic flow or intensity is explained by the chosen independent variables of time, day, density and stretch of the road. It further showed that there was a significant amount of unexplained variation of 42% which was probably due to other causes of traffic like road infrastructure, weather, festive days, among others. The developed predictive model therefore demonstrated high accuracy in forecasting traffic intensity, providing valuable insights for traffic management in Kampala.

Testing Goodness of fit

Using the Chi-square method of determining the goodness of fit, the expected outcomes were hypothesized as shown”

- Null Hypothesis: (Ho), $P_1=P_2$, the predictions are the same as observed values
- Alternative hypothesis: (Ha), $P_1 \neq P_2$, the predictions are not the same as observed values

P1 being the observed and *P2* being the predicted values.

Table 3: Sample calculation of the chi-square

OBSERVED	PREDICTED	(P2-P1)	$(P2-P)^2$	$(P2-P)^2/P1$
263	248	14.973	224.205	0.851
217	231	-14.140	199.927	0.923
228	214	13.870	192.368	0.845
216	202	13.284	176.475	0.819
193	178	15.117	228.510	1.182
198	215	-16.415	269.450	1.359
262	240	22.449	503.945	1.923
232	226	5.950	35.406	0.153
234	248	-13.993	195.798	0.838
294	284	9.640	92.926	0.316
114	119	-5.060	25.603	0.225
121	129	-8.262	68.257	0.566
131	133	-2.598	6.749	0.052

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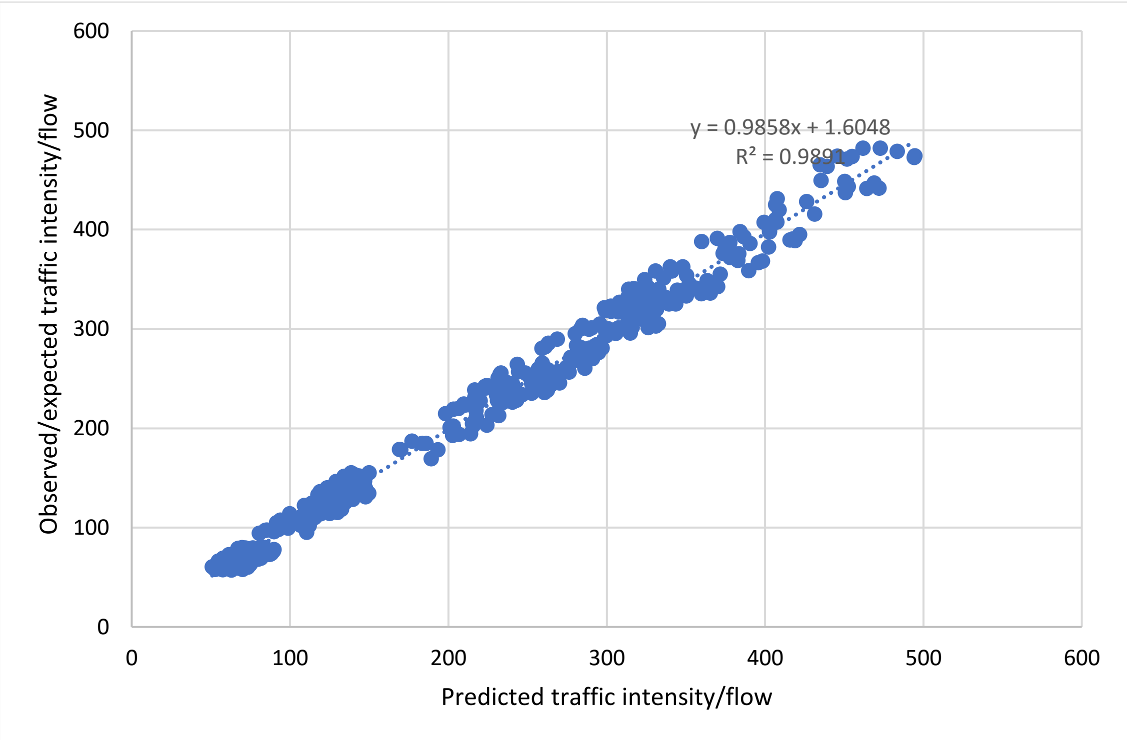
OBSERVED	PREDICTED	(P2-P1)	$(P2\text{-}P)^2$	$(P2\text{-}P)^2/P1$
100	114	-13.990	195.723	1.962
147	135	11.979	143.501	0.978
130	115	14.772	218.202	1.679
60	61	-0.786	0.618	0.010
87	74	12.383	153.335	1.772
68	59	8.195	67.152	0.995
58	69	-11.340	128.605	2.231

Table 3 shows sample predicted and observed values of the traffic flow and how the chi-square was obtained. Using Excel formula, =CHISQ.INV.RT(0.05,427), a critical value of 476 was obtained, this was compared with the Chi-square value obtained in the Excel table as 347.Since the Chi-square value of 347 was less than the critical value of 476, then the Null hypothesis was not rejected, therefore the predicted values of traffic intensity/flow relate closely with the observed values of traffic intensity or flow.

Observed and predicted values analysis

Plotting the observed values against predicted traffic intensity/flow values in Figure 5 showed a linear relationship between the two, confirming the goodness of fit for the developed model. The high R-square value of 0.989 showed a great connection between the two and therefore predicted traffic intensity could easily tell the traffic situation on the road at a given point in time. This as well showed that the developed predictive model therefore demonstrated high accuracy in forecasting traffic intensity, providing valuable insights for traffic management in Kampala.

Figure 5: Observed traffic flow/intensity against predicted traffic flow or intensity



Mean Absolute Percentage Error

The acceptable percentage error was calculated in Excel as shown in Table 4 above using Mean Absolute Percentage Error. It was obtained as 6.4% deviation from the expected traffic intensity.

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Table 4: Calculation of the Mean Absolute Percentage Error

Expected(E)	**Predicted (P)**	***Residuals(P-E)***	***(P-E)^2***	***(P-E)^2/E***		**Absolute P-E**	**(Absolute P-E)/E**	**Absolute percentage error**
263	248	14.973	224.205	0.851	0.057	15	0.057	5.684
217	231	-14.140	199.927	0.923	-0.065	14	0.065	6.529
228	214	13.870	192.368	0.845	0.061	14	0.061	6.096
216	202	13.284	176.475	0.819	0.062	13	0.062	6.162
193	178	15.117	228.510	1.182	0.078	15	0.078	7.822
198	215	-16.415	269.450	1.359	-0.083	16	0.083	8.277
262	240	22.449	503.945	1.923	0.086	22	0.086	8.567
232	226	5.950	35.406	0.153	0.026	6	0.026	2.567
234	248	-13.993	195.798	0.838	-0.060	14	0.060	5.988
294	284	9.640	92.926	0.316	0.033	10	0.033	3.282
114	119	-5.060	25.603	0.225	-0.044	5	0.044	4.441
121	129	-8.262	68.257	0.566	-0.069	8	0.069	6.851
131	133	-2.598	6.749	0.052	-0.020	3	0.020	1.989
100	114	-13.990	195.723	1.962	-0.140	14	0.140	14.023
147	135	11.979	143.501	0.978	0.082	12	0.082	8.168
130	115	14.772	218.202	1.679	0.114	15	0.114	11.364
60	61	-0.786	0.618	0.010	-0.013	1	0.013	1.305
87	74	12.383	153.335	1.772	0.143	12	0.143	14.309
68	59	8.195	67.152	0.995	0.121	8	0.121	12.139

This margin error indicated that, on average, the predicted traffic intensity/flow values may deviate from the actual observed values by approximately 6.4%. This level of accuracy is considered good since it is less than 10%, between 10% and 20%, it is considered a reasonable forecast (Walker, 2021).This shows that the model can perform well in traffic flow predictions on Kampala roads.

DISCUSSIONS

The findings established a relationship between the variables of the density, flow, time, headways at the selected road sections. This relationship was represented by a relative R-square value of 0.58 that showed strong dependencies of variables to each other.

The traffic flow tends to decrease as the time progresses in the day, this was due to the effect of rush hours and changes in driver behaviour. During rush hours, traffic flow increases as more vehicles are on the road, but as the day moves beyond these peak times, traffic flow typically decreases due to reduced travel demand between midday and afternoon hours.

The model also shows that changing from weekdays to weekend, the flow decreases by about 29%, as there is less people that come to work on weekends.

As density increases by 1%, the flow also increases by 1.5% over time. This aligns with traffic flow diagrams highlighted by a study by Lele et al. (2020) which proposed that as traffic density increases, the flow of vehicles also increases until a certain point, known as the maximum flow. Beyond the capacity, further increases in density leads to reduced flow and eventually traffic congestion.

The findings also illustrated that the developed model can accurately predict the traffic intensity or flow on the road at a given time to a small margin of MAPE estimated at 6.4%. This meant that model's predictions are reliable and can be used effectively to assess the traffic conditions on roads in Kampala.

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CONCLUSIONS

The study concluded that traffic flow characteristics in Kampala depend on both microscopic and macroscopic factors, highlighting the complex nature of traffic dynamics. The density contributed the most of all the traffic characteristics to the traffic flow problem.

The hypothesis *(P_1=P_2)*, was tested using the chi square method as shown in Table 3 and

the null hypothesis which shows that the predictions are the same as observed values was not rejected since the predicted values from the equation were related to the data collected from the road sections

- Null Hypothesis: (Ho), P_1=P_2, the predictions are the same as observed values
- Alternative hypothesis: (Ha), $P_1 \neq P_2$, the predictions are not the same as observed values

P1 being the observed and *P2* being the predicted values.

The predictive model developed in this study offers a valuable tool for urban planners and city authorities in managing traffic flow in Kampala CBD by being able to forecast the trends. To address congestion in Kampala effectively, a comprehensive approach is necessary, including improvements to public transportation and promotion of non-motorized modes.

RECOMMENDATIONS

The following recommendations were deduced:

Policy recommendations

- The researcher suggests utilizing the developed model in equation 5 to enhance intelligent transportation solutions that can be incorporated in the daily development of how to handle city traffic since the model can predict traffic flow with high margin of accuracy.
- The traffic police department should promote and encourage more cargo vehicles to move during weekends as lesser traffic is expected on the roads by 29%.
- Commuters and police traffic department should also use the developed model to identify traffic pattern due to its reliability and low margin of error at 6.4%.
- Since the findings identify traffic density as a major cause of congestion, Kampala Capital City Authority (KCCA) should enforce public transportation to reduce reliance on personal vehicles which reduces vehicle density within the city center and subsequently reduces congestion.
- In order to take into account, the real-time traffic volume incident data resulting from driver behavior and infrastructural factors on roads like Jinja Road and Entebbe Road, the traffic police department should provide special support for the design and implementation of data-driven traffic management models that are dynamic enough, like the one developed in this study.

Future research recommendations

- There is need for more research on how to integrate this data into the intelligent traffic system so that unmanned traffic intersections can recognize jam or a free flow based on their features. Additionally, this will increase the likelihood of driverless vehicles.
- Additional studies incorporating more variables such as weather conditions and road incidents to refine the predictive model and cater for the unexplained variation of 42%, should be conducted.

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