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EXPLORATION OF THE EFFECTS OF HETEROGENOUS VEHICLE COMPOSITION ON URBAN ARTERIAL TRAFFIC FLOW ATTRIBUTES

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ABSTRACT

The streets of Dhaka experience significant congestion due to the substantial volume of vehicles traversing them daily. The diverse mix of vehicle types, or heterogeneity, increases the complexity of traffic flow and contributes to the broader issue of traffic congestion. Given the saturation of the surrounding land, there is limited potential for expanding road capacity through infrastructure development. Therefore, optimization techniques for the existing road network need to be implemented to enhance the overall traffic flow condition. In light of this, the principal aim of this paper is to identify the vehicle types that have the most significant influence in adversely impacting the traffic flow attributes including relative delay, density, and average speed of vehicles on the urban arterial roads of Dhaka. The Abdul Gani road beside the Bangladesh Secretariat was chosen as the study area, and one hour of traffic video data in the peak period was collected to develop a microsimulation model in PTV VISSIM. The model was calibrated by tuning the Weidemann 99 car-following model parameters along with lane-changing behaviour, lateral movement, and similar parameters. The model was validated by comparing the simulated and real-time traffic flow and generating GEH Statistic for each of the approaching links of the study network. The GEH values were determined to be under 5% which deemed the simulation model appropriate for further analysis. Hypothetical combinations of vehicle composition were developed by using the Latin Hypercube Sampling (LHS) method. The LHS Python code was tasked to create 500 combinations of relative traffic flow percentages of the vehicle types. Each of the combination was simulated in the base model to obtain the aforementioned traffic flow attributes. A Random Forest algorithm was applied to the output dataset acquired from VISSIM simulations to generate feature importance plots and to rank the vehicle types according to their contribution to the values of traffic flow attributes. The Random Forest Regressor technique was also utilized to create linear relationship equations between the relative percentage flow of vehicle types and the output variables. The results suggested that buses had the most significant impact on traffic density and relative delay of the road network. On the other hand, rickshaws presented the most threat to the average speed as they had the most impact in decreasing the overall speed of the simulated links. Besides these, correlation heatmap and partial dependence plots were also generated to better understand the traffic dynamics and the relationship between the types of vehicles. The findings of this study will help transportation planners and decision-makers understand the impact of different types of vehicles on traffic flow performance and in making crucial decisions regarding congestion management strategies.

Keywords: *PTV VISSIM, Random Forest, Simulation, Vehicle Composition, Congestion Management*

1. INTRODUCTION

Traffic congestion is one of the most formidable challenges that plague the streets of Dhaka. As a nation with a rapidly increasing population and growing urban centers, the negative effects of congestion extend far beyond what meets the eye, impacting economic productivity, environmental sustainability, and overall quality of life. Exploration of strategies for mitigating or marginalizing traffic issues has been a topic of interest for transportation engineers all over the world for a long time. For developing countries, where the congestion problems are at their worst, transportation professionals are conducting in-depth research regarding both policy-related and technological approaches. The exploration of effective strategies to alleviate congestion in Bangladesh is an absolute necessity and thus requires comprehensive studies into the dynamics of traffic movements, especially in metropolitan cities like Dhaka.

Traffic mixtures usually define the types of vehicles in a certain road network. Although there exist many classifications of traffic mixture and the definition is perceived differently in diverse parts of the world, all the classifications can be put into two major categories – Homogenous Traffic Mix and Heterogeneous Traffic Mix. Homogeneous mix refers to a situation where the majority of vehicles on the road share similar properties such as size, speed, and functionality. In heterogeneous traffic mixtures, the road is shared by a diverse range of vehicles with varying sizes, speeds, and operational characteristics. In the context of Bangladesh, the heterogeneous traffic mix includes motorized vehicles such as cars, buses, and motorbikes as well as non-motorized vehicles such as rickshaws, bicycles, etc. Due to the immense difference in characteristics of these vehicle types, the traffic flow analysis can be difficult to apprehend. It is imperative to understand the impacts of all types of vehicles on the overall traffic performance so that informed policy-related or technology implementation-related decisions can be taken by transportation planners. Thus, as traffic problems due to heterogeneous traffic mixtures increased, the research into the effects of varying traffic compositions gained popularity among traffic researchers, especially in developing countries like Bangladesh.

Traffic flow in urban signalized arterials can be estimated to have a high degree of manoeuvrability and lane changing as a result of a mixture of fast-moving and slow-moving vehicles (Arasan & Koshy, 2005). This is one of the core reasons behind the toughness of establishing mathematical relationships between traffic flow characteristics and traffic volume. Due to the transitional nature of the functional relationship that governs most traffic variables in mixed traffic conditions, the relationship will have to incorporate further complexity (Khan & Maini, 1998). Establishing a relationship between varying traffic composition and flow characteristics would require huge amounts of data which would add to the complexity. To relieve the data deficit for such studies, traffic simulation models can be a suitable alternative to real-time data. In recent years, microsimulation models have proven to be quite successful in emulating real-world traffic scenarios for mixed traffic conditions in Dhaka (Ahmed et al., 2023) (Hoque & Naz, 2023). Similar models have been utilized to derive the capacity of particular highways (Anamika & Arun, 2015) and to plot speed-flow curves (Shukla & Chandra, 2011). Chandra et al. (2015) also explored the variation of roadway capacity with varying traffic compositions for mixed traffic conditions. However, there exists a significant research gap in the exploration of the effects of varying traffic compositions of mixed traffic conditions that include non-motorized vehicles on traffic flow attributes such as density, average speed, etc.

This paper aims to delve into the dynamic effects of different relative traffic compositions on traffic flow attributes using microsimulation tools. Firstly, real-world data is collected to create a proper simulation model through calibration and validation. Secondly, various scenarios of traffic compositions are created within the simulation model and the data collected from simulations is capitalized in generating linear regression models that establish the relationship between different types of vehicles and traffic flow attributes. Thirdly, the study also demonstrates the most influential vehicle types that dictate different significant traffic flow characteristics and provides insight into the roles of different types of vehicles on overall urban arterial traffic flow under heterogeneous mix traffic conditions. Lastly, a sensitivity analysis is conducted to understand the nature of change in traffic flow attributes due to different levels of a particular vehicle type on the road network.

2. METHODOLOGY

The progression of this study is divided into three major parts – Traffic data collection and simulation model development, Vehicle composition sampling and simulations, Random Forest Algorithm and sensitivity analysis. Each segment of the major parts is described in this paper for a continuous flow of information.

2.1 Data Collection & Network Coding

The site selected for this study is the Abdul Gani Road adjacent to the Bangladesh Secretariat and near to Old High Court Building. The level of heterogeneity, the all-encompassing traffic movement, and the vast amount of traffic in this particular road network made this a perfect area for this study. Two types of data were collected from the study site – Traffic count data and Geometric data.

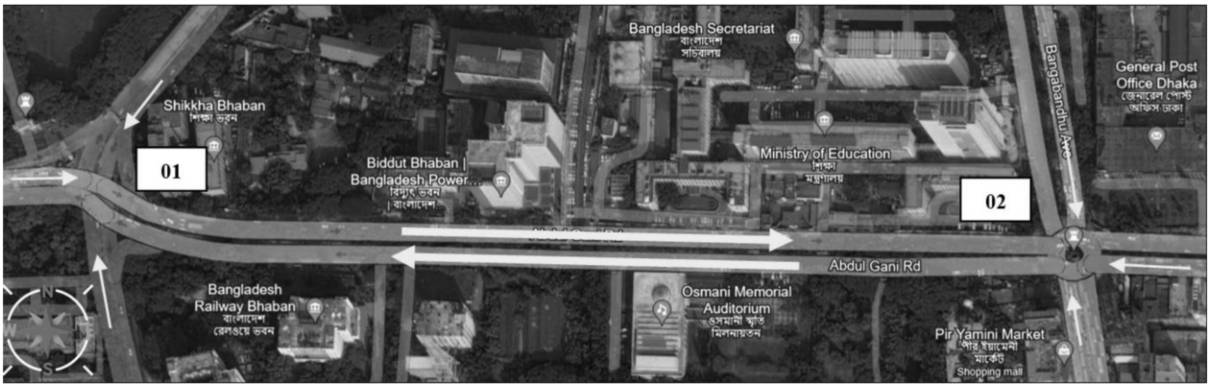

Figure 1: Google Earth View of Study Site

The data were collected on a Monday morning from 8:00 AM to 10:00 as that is generally considered to be the peak hour. The traffic data consists of the types of vehicles, the number of vehicles traveling through the road network along with their routes, and the average signal timings of the intersections. The traffic count was taken only for the vehicles entering Abdul Gani Road. The geometric data includes the number of lanes and lane width on each of the roads. For easier comprehension, the two intersections at the two endpoints of the study road are numbered along with the number of intersection-approaching roads in Figure 1. The collected data is showcased in Table 1.

Table 1: Traffic Count and Geometric Data

Intersection	Approach Direction	Total Vehicles	Number of Lanes	Lane width (meters)	Green Signal Times (seconds)
1	North	656	2	3.5	Always Green
	West	718	3	3.3	51
	South	707	3	3.3	33
2	North	667	3	3.45	42
	East	583	3	3.5	58
	South	614	3	3.3	41

The traffic survey was conducted by using video cameras placed at strategic points to capture the movement of all the vehicles within the intersection. The necessary traffic data including vehicle composition was manually extracted from the video footage. The geometric information was gathered from continuous field surveys using a pedometer. If Intelligent Transportation System technologies are implemented, traffic data collection can become much easier. (Naz & Hoque, 2023)

After the completion of the data collection process, the whole network was modeled in the VISSIM graphical user interface. The straight uninterrupted roads were modeled using the link tool and the connecting roads were generated by using connectors. The curves of the roads were fixed by introducing an appropriate number of intermediate points. The conflict areas were resolved and signal heads were put into the model by studying the actual movement of traffic from video footage. To represent all the types of vehicles accurately, the default 3D models that resonated the most with the traffic of the study site were chosen. As VISSIM default models did not contain a 3D model of a rickshaw, a separate model was introduced to the interface to simulate their movement.

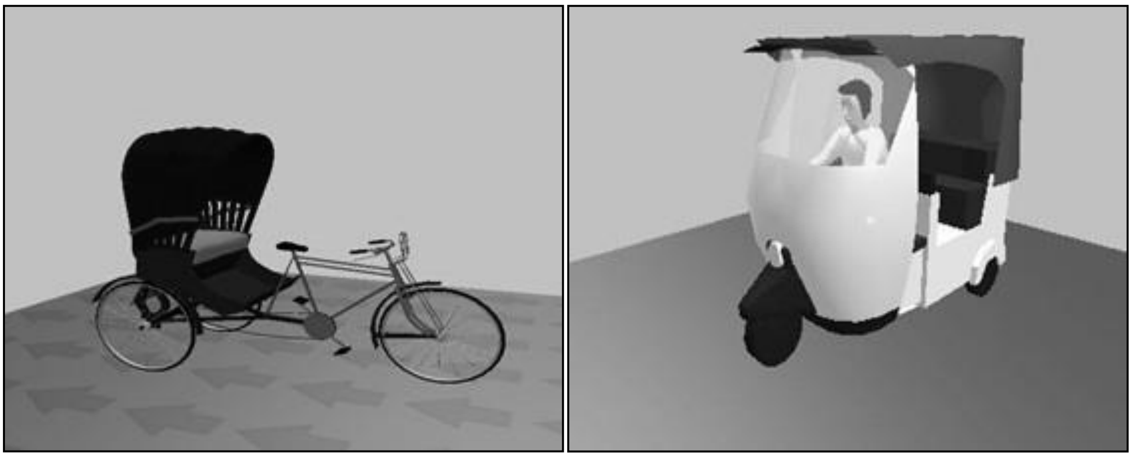

Figure 2: Vehicle 3D Models

The desired speed distribution, maximum and minimum acceleration, and other similar parameters of each vehicle type were taken from video footage and validated by literature (Dutta & Ahmed, 2019) that focused on exploring these parameters for mixed traffic conditions. Bicycles were ignored in the model as the amount was quite low to cause any significant change in the output values of this study.

2.2 Calibration & Validation

The calibration of a microsimulation model is one of the most challenging aspects of studying mixed traffic conditions (Mashrur & Hoque, 2016). For this particular study, the mixed traffic consisted of motorized vehicles like cars, trucks, and buses as well as non-motorized vehicles like bicycles and rickshaws which only added to the complexity of the calibration process. After iterations of different combinations of Wiedemann 99 Car Following Model parameters that incorporated values taken from (Shukla & Chandra, 2011) (Budhkar & Maji, 2022) (Siam et al., 2018), the combination that yielded the best results was selected for this study (Table 2). The lane-changing behavior parameters, lateral movement parameters, and other similar calibration parameters were also adjusted using a similar approach.

Table 2: Car Following Model Calibration Parameters

CC0	CC1	CC2	CC3	CC4	CC5	CC6	CC7	CC8	CC9
1.4	0.9	2.73	-1.69	-1.05	2.05	7.34	0.38	3.53	0.76

After the calibration process, the accuracy of the model has to be checked by comparing the simulated data and the real traffic data. Various measures of goodness of fit can be undertaken to validate the simulation model. This study utilizes the GEH (Geoffrey E. Havers) statistic for validation purposes as this has been widely used in traffic engineering, traffic forecasting, and traffic modeling to compare sets of traffic volumes (Balakrishna et al., 2007) (Chu et al., 2011). The formula used to determine this statistic can be defined by equation (1).

$$GEH = \sqrt{\frac{2(M - C)^2}{(M + C)}} \tag{1}$$

Here –
M – Simulated traffic volume
C – Real-world traffic volume

Different values of GEH can give different insights about the goodness of fit of the model. GEH values below 5 can deem the simulation model to be a good fit. Values ranging from over 5 to 10 suggest that the model should be looked into more for a better fit. GEH values above 10 are not acceptable for any traffic condition and are suggestive of recalibration. After using the car following model parameters of Table 2 and other acceptable calibration parameters, the GEH values for each of the exits of the simulated network are showcased in Table 3.

Table 3: GEH Values

Intersection No	Exit Direction	GEH Value
1	North	3.925615
	West	4.092728
	South	4.309513
2	North	3.373536
	East	3.627198
	South	3.541853

All the values of GEH are within the acceptable range and thus the simulation model can be considered to be able to emulate traffic conditions of the study site accurately. A still shot of the calibrated and validated simulation model is shown in Figure 3.

Figure 3: VISSIM Simulation Model

2.3 Vehicle Composition Sampling

The calibration and validation process indicated that the traffic pattern and behavior of the study site are now being accurately reflected in the simulation model and the model is now prepared for experimentation. To achieve the target objective of this paper, the Latin Hypercube Sampling (LHS) method was adopted to sample the relative flow of traffic in the road network. The LHS method can provide an efficient way of sampling variables from their distributions (Iman and Conover, 1980). For this study, the range of the relative flow of each type of vehicle was set to 0 to 1 in the sampling process for each combination of traffic composition. But in each of the combinations, the total relative flow was set to be 1. A total of 500 combinations of vehicle compositions were set to be generated using Python coding of the sampling method and for each of the combinations traffic flow attributes of the Abdul Gani Road were collected for further analysis. The types of vehicles and 5 sample output combinations are showcased in Table 4.

Table 4: LHS Sampling Output Example

Combination	Car	Bus	Motorbike	CNG	Truck	Micro	Rickshaw
1	0.095	0.01	0.264	0.167	0.142	0.09	0.232
2	0.164	0.244	0.052	0.168	0.243	0.028	0.101
3	0.225	0.144	0.242	0.059	0.122	0.144	0.064

2.4 Traffic Flow Attributes

VISSIM microsimulation tool can determine various traffic flow variables including travel time, queue length, delay, speed, density, etc. for any complex road network. Varying traffic composition can be estimated to have a significant effect on each of these variables but for this study, only three traffic flow variables have been chosen to be the epicenter of analysis. These variables are –

Traffic Density: This refers to the number of vehicles occupying a specific length of roadway. Here the specific length of the roadway was the length of Abdul Gani Road which was about 630 meters. The formula to define density is shown in equation (2).

$$Density = \frac{Number\ of\ Vehicles}{Length\ of\ Road\ Segment} \tag{2}$$

Relative Delay Percentage: This is used to express the delay experienced by a vehicle in comparison to an ideal or free-flow condition. The formula can be defined as equation (3).
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$$Relative\ Delay\ Percentage = \frac{Actual\ Delay - Free\ Flow\ Delay}{Free\ Flow\ Delay} *100 \tag{3}$$

Average Speed: This variable refers to the average speed of vehicles within the study area. The unit for this variable was kilometres per hour. The formula for calculating average speed is:

$$Average\ Speed = \frac{Total\ Distance\ Traveled\ by\ Vehicles}{Total\ Travel\ Time} \tag{4}$$

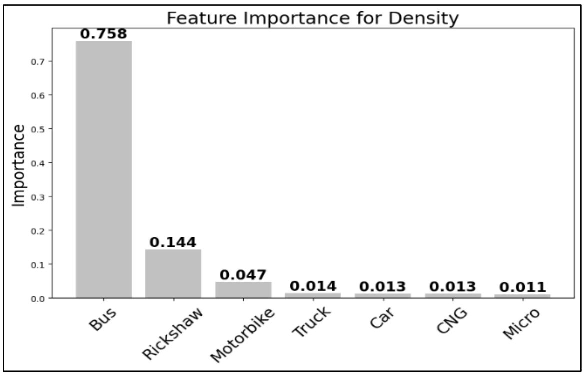
All the aforementioned variables were calculated for both the two-directional links of Abdul Gani Road and the output values were averaged to determine a single value for traffic composition comparison analysis. A sample of the output data against the vehicle composition is shown in Table 5.

Table 5: Vehicle Composition and Output Attributes

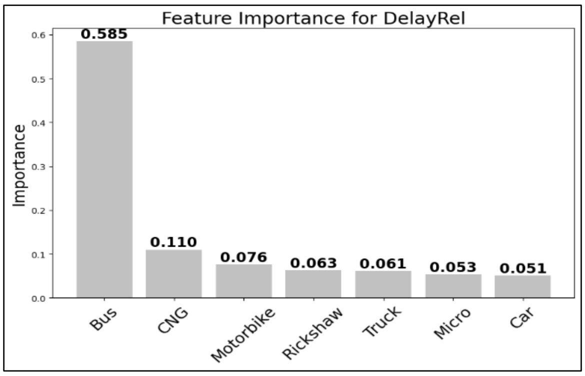
No.	Car	Bus	Motor-bike	CNG	Truck	Micro	Rickshaw	Density	Relative Delay	Average Speed
1	0.095	0.01	0.264	0.167	0.142	0.09	0.232	443.76	64.20%	5.48
2	0.164	0.244	0.052	0.168	0.243	0.028	0.101	309.36	71.63%	4.90
3	0.225	0.144	0.242	0.059	0.122	0.144	0.064	365.77	73.97%	5.19
4	0.225	0.144	0.242	0.059	0.122	0.144	0.064	365.76	73.97%	3.83
5	0.093	0.196	0.124	0.027	0.099	0.171	0.290	370.90	72.65%	5.05
6	0.252	0.002	0.168	0.162	0.19	0.062	0.164	470.21	69.73%	4.18
7	0.197	0.185	0.095	0.130	0.095	0.112	0.186	375.65	74.08%	4.31
8	0.178	0.217	0.020	0.059	0.179	0.177	0.170	326.76	73.28%	5.76
9	0.103	0.302	0.150	0.038	0.184	0.185	0.038	267.10	70.34%	4.05
10	0.055	0.064	0.280	0.036	0.239	0.086	0.240	498.59	72.89%	3.80
11	0.190	0.190	0.063	0.015	0.032	0.254	0.256	369.66	74.55%	4.12
12	0.168	0.148	0.014	0.126	0.084	0.201	0.259	378.97	71.49%	4.28
13	0.208	0.167	0.102	0.132	0.174	0.028	0.189	377.17	73.02%	4.50
14	0.252	0.190	0.061	0.114	0.134	0.084	0.165	344.29	72.76%	4.90
15	0.284	0.049	0.046	0.140	0.125	0.266	0.090	397.34	73.46%	4.62
16	0.181	0.144	0.080	0.219	0.170	0.059	0.147	377.11	72.30%	4.64
17	0.158	0.013	0.114	0.222	0.221	0.012	0.260	487.09	67.45%	4.44
18	0.029	0.168	0.262	0.132	0.048	0.203	0.158	394.76	74.24%	4.26
19	0.069	0.290	0.092	0.080	0.12	0.167	0.182	304.03	73.33%	5.36
20	0.203	0.123	0.048	0.347	0.175	0.036	0.068	375.91	70.78%	5.21

2.5 Random Forest Algorithm

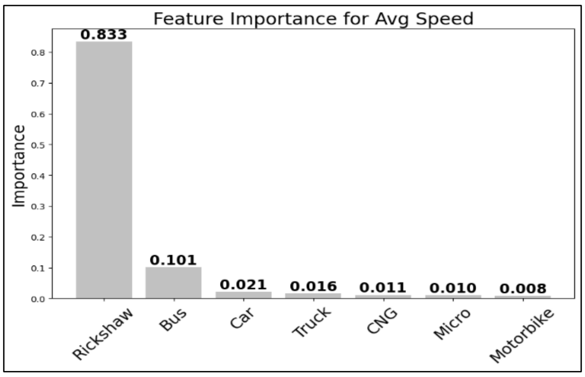
Random Forest (RF) is a powerful technique for conducting a feature importance analysis (Ali et al., 2022). After the simulated results of 500 combinations were collected, a RF Algorithm was utilized to analyse the impact of each type of vehicle on the traffic flow attributes. A feature importance plot was generated for each of the output parameters to determine the most impactful type of vehicle affecting that certain traffic flow characteristic as showcased in Figure 5.



(a) Density



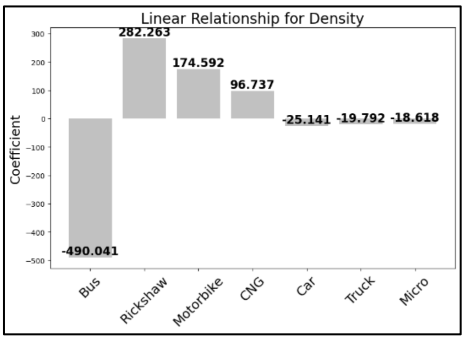
(b) Relative Delay



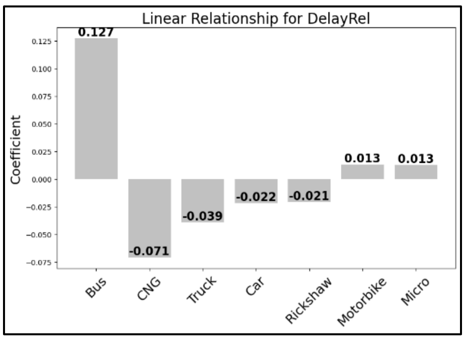
(c) Average Speed

Figure 5: Feature Importance Plots

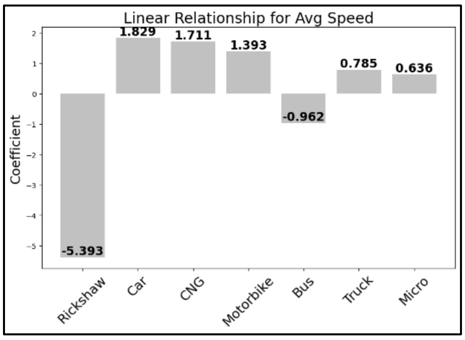
All the data used for this analysis is quantitative data for which a Random Forest Regressor technique was applied for the feature importance plots. This technique can also be utilized in deriving linear relationships between the input and output variables. For this particular analysis, if we take the relative percentage of each type of vehicle to be the input variables and the density, average speed, and relative percentage delay of the road network to be the output variable, then linear relationships can be generated using the Random Forest Regressor method. The coefficient values can be visualized by generating vehicle types vs co-efficient plots as shown in Figure 6.



(a) Density



(b) Relative Delay



(c) Average Speed

Figure 6: Vehicle Types vs Coefficients

The relationship between these sets of input and output variables are also showcased in equation (5), (6), and (7).

*Density= -490.041*B+282.263*R+174.592*Mo+96.737*CNG-25.141*C–19.792*T–18.618*Mi* (5)

*Relative Delay= 0.127*B-0.071*CNG-0.039T-0.022*C-.021*R+0.013*Mo+0.013*Mi* *(6)*

*Average Speed= -5.393*R-1.829*C+1.711*CNG+1.393*Mo-0.962*B+0.785*T+0.636*Mi* *(7)*

Here,
B= Relative Percentage Flow of Buses on the road network
R= Relative Percentage Flow of Rickshaws on the road network
Mo= Relative Percentage Flow of Motorbikes on the road network
CNG= Relative Percentage Flow of CNG on the road network
Car= Relative Percentage Flow of Cars on the road network
Truck= Relative Percentage Flow of Buses on the road network
Micro= Relative Percentage Flow of Microbuses on the road network

3. RESULTS & DISCUSSIONS

The analysis of the effect of different types of vehicles on the traffic flow performance revealed key insights into the dynamic nature of traffic flow in mixed traffic conditions. The feature importance plot for traffic density suggests that the most significant type of vehicle that increases traffic density is the bus. The importance value for the bus was determined to be 0.758 making it far more significant in increasing traffic density as the second highest importance value was 0.144 for the rickshaw. Truck, Car, CNG, and Microbus types of vehicles can be deemed to be inconsequential to the traffic density as their importance value was respectively 0.014, 0.013, 0.013, and 0.011. But the motorbike had an importance value of 0.047 making it the third highest out of all the vehicle types.

The feature importance plot for relative delay also showed a similar result compared to the density plot as one of the vehicle types was far more significant than other types in increasing relative delay. Buses on the road network were also the most crucial factor in increasing the relative delay of the Abdul Gani Road. But unlike the density plot where some of the vehicle types could have been considered to be insignificant, in the relative delay plot all the vehicle types except buses had a similar effect on the traffic performance. The relative delay values of the CNG, Motorbike, Rickshaw, Truck, and Micro were found to be 0.110, 0.076, 0.063, 0.061, 0.053, and 0.051 respectively suggesting similar effects on the traffic flow performance.

From the feature importance plot, the average speed of traffic in the study network was found to be very reliant on the number of existing rickshaws. The importance value for rickshaws was found to be 0.833 suggesting a huge effect on the traffic flow attribute. The second most significant vehicle type for this traffic flow variable was the bus for which the value was 0.101. But the rest of the vehicle types had similar importance on changing the average speed of traffic with the importance value for car, truck, CNG, micro, and motorbike to be respectively 0.021, 0.016, 0.011, 0.010, and 0.008.

The linear relationship between the relative percentage flow of vehicle types and the traffic flow attributes showcases the resonance between the regression coefficients and feature importance values. However, from the regression equations, the positive or negative effect of each vehicle type can be properly identified. In the equations, a negative value suggests that a particular input variable is responsible for lowering the value of the output attribute. A positive will suggest the opposite as it indicates that a certain input variable increases the output value with the increase of its values. The density equation reveals that buses are the most significant contributor to lowering the traffic density of the road network as the co-efficient of the bus was found to be -490.041. But from the relative delay equation, the co-efficient of the bus was the highest but the value was positive indicating that the increase in the number of buses on the road network would increase the relative delay most significantly compared to others. The coefficient of rickshaws in the average speed equation was found to be -5.393 which would mean that the increase in the relative percentage of rickshaws would significantly decrease the average speed of the road network. The results from the Random Forest Regression equations and the Random Forest Feature Importance plots are similar thus validating the analysis process.

As the dataset generated from 500 simulations contains multiple variables, understanding the inner relationships between pairs of variables can be challenging. In this case, correlation heatmaps may help in conducting a multivariate analysis by displaying the correlation structure in a single plot. To conclusively determine if a relationship between the vehicle types exists while generating the output variables, a correlation heatmap including all the input and output variables was plotted as shown in Figure 7.

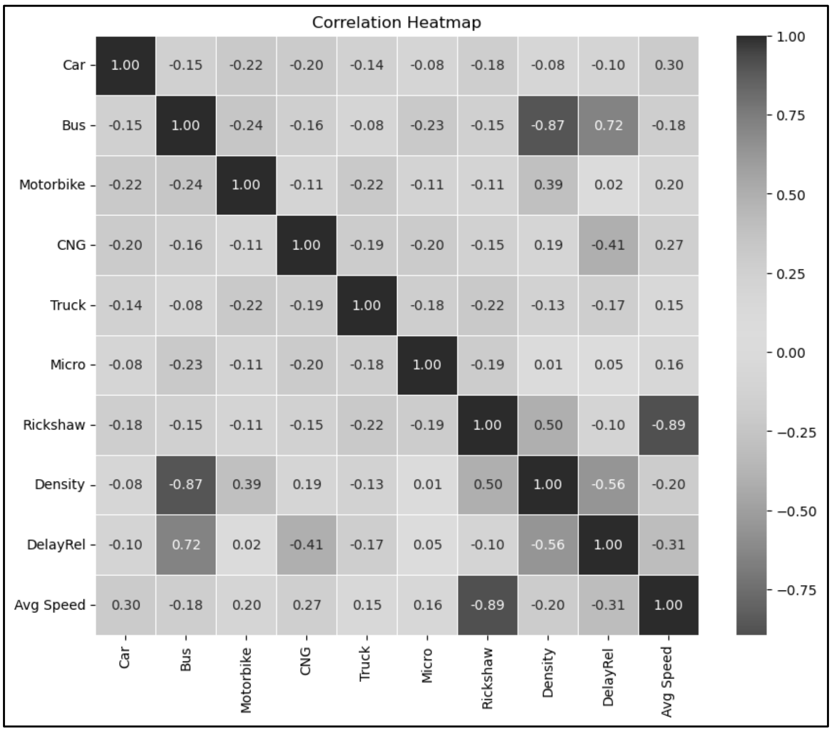
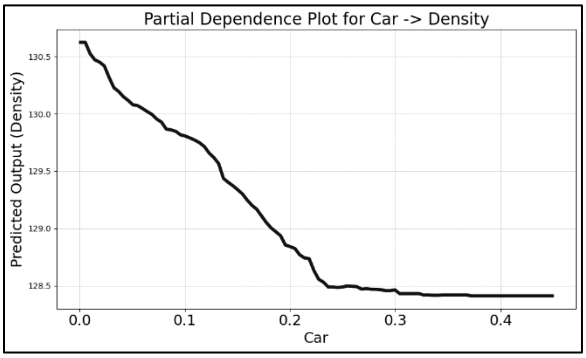
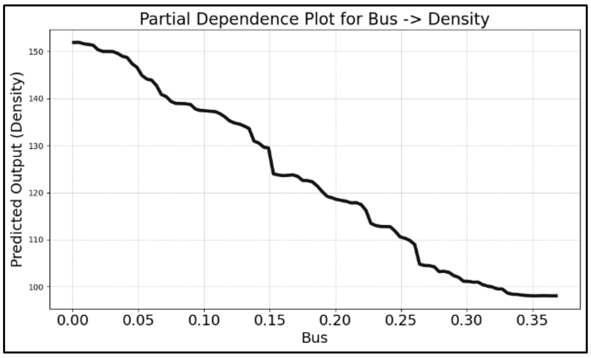


Figure 7: Correlation Heatmap

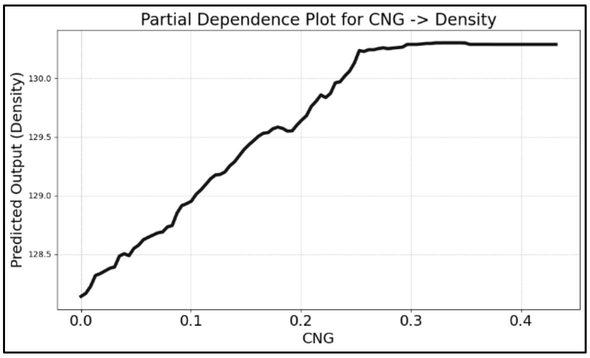
In a correlation heatmap, the expected values are between 1 and -1. A value of 1 suggests a perfect positive correlation, 0 suggests no correlation, and -1 suggests a perfect negative correlation. All the correlation values between the input variables can be observed to be between -0.0 to -0.03 suggesting that there is little to no correlation amongst the input variables. Besides the insight gathered from the correlation heatmap, the observed values also suggest that the dataset is good enough for analysis and doesn't contain any unnatural or unpredictable relationships between the input variables. Although, he values for the output variables indicate that there is a strong relationship between traffic density and relative delay of traffic, this value is acceptable as there is a simple cause-and-effect relationship between these two variables. Thus, this correlation value of -0.56 is not cause for concern as this is quite natural and predictable.



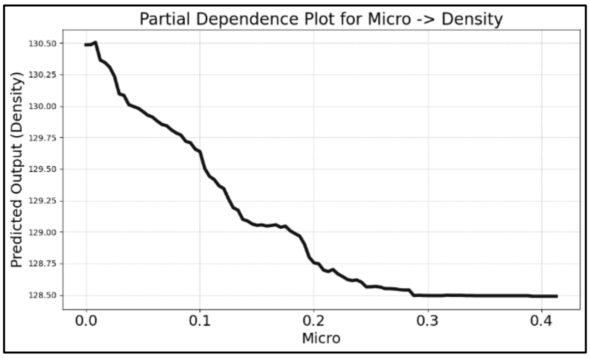
(a) Car



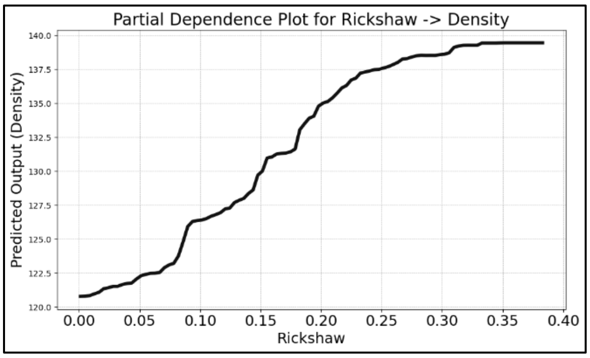
(b) Bus



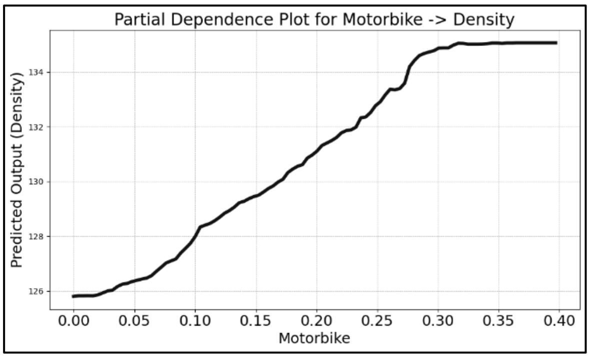
(c) CNG



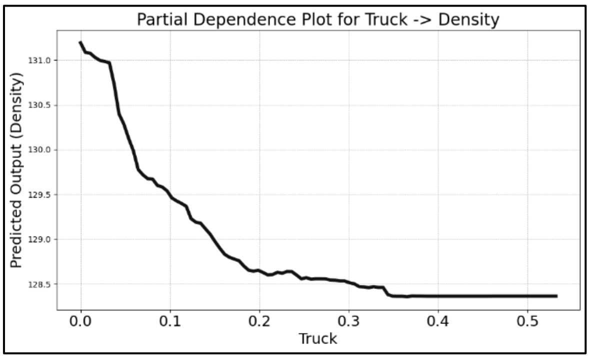
(d) Micro



(e) Rickshaw



(f) Motorbike



(g) Truck

Figure 8: Partial Dependence Plots for Density Output

For a further understanding of the traffic dynamics in mixed traffic conditions, partial dependence plots for each of the input variables against each of the output variables were plotted. Only the plots against the density output variables are showcased in Figure 8 as the partial dependence relationship between the input variables and the other output variables can be explained through these plots and the linear relationship equations as well.

The Partial Dependence Plot (PDP) of Bus against Density showcases that if the relative percentage flow of buses increases, the traffic density of the road network will also decrease. The core reason behind this is the large negative coefficient of Buses demonstrated in the linear relationship equation (5). The density is observed to be very low when the relative percentage flow of bus is increased to nearly 0.30. A similar trend can be seen in the PDP plots of Car, Micro, and Truck. However, as the number of cars, microbuses, and trucks increase on the roads, the density of the network doesn't go down as quickly as for buses. Thus, these particular PDPs showcase a valuable insight into the dynamic effect of these vehicle types on the traffic flow performance.

From the PDP plots of vehicle types vs density of CNG, Motorbikes, and Rickshaws, it can be seen that the density increases as the relative percentage flow of these vehicle types increases. The effect is not that much significant but the trend lines of these plots suggest that if the number of these vehicle types are increased, the total vehicles on a particular segment of a road can be increased as well. However, for all these plots, when the percentage flow reaches the value around 0.25 to 0.30, the density reaches a somewhat stagnant value and doesn't that much rapidly anymore.

4. CONCLUSIONS

This research paper aimed to address the issue of traffic congestion and emphasized the need to understand the traffic dynamics of mixed traffic conditions existing on the streets of Dhaka. The study focused on the Abdul Gani Road near the Bangladesh Secretariat and a VISSIM microsimulation model was created to emulate the traffic flow through the collection of traffic and geometric data. After a successful calibration and validation process, the Latin Hypercube Sampling Method was adopted to create a dataset of 500 combinations of relative flow percentages of various vehicle types. After gaining the output traffic attributes from the 500 simulations that used the aforementioned 500 combinations, a Random Forest Algorithm was employed to gain feature importance plots. Aside from these, a Random Forest Regressor technique was utilized to plot and generate linear relationships between vehicle type flow percentage and output variables that included traffic density, relative delay, and average speed of the road network. Correlation heatmaps along with partial dependence plots were also generated to better understand the traffic dynamics. This research contributes to diminish the knowledge gap on the effects of varying traffic compositions, especially considering non-motorized vehicles, on traffic flow attributes in mixed traffic conditions. The findings of this paper will contribute to the field of transportation engineering by offering a better understanding of the intricate interactions between diverse vehicle types and traffic flow attributes. The results may provide valuable guidance for policymakers and transportation planners in coming up with solutions to mitigate traffic congestion in mixed traffic conditions.

Although the progression of this research paper contained meticulous steps, there are a few limitations that need to be addressed. The pedestrian movement in the road network was not taken into account while generating the microsimulation model. The study site contained a lot of on-street parking but the simulation model did not incorporate the parking and as a result, the difference of the outputs due to the presence of roadside friction was not considered. In future studies, roadside parking should be taken into account while emulating the traffic movement in mixed traffic conditions and conducting further analysis using simulation methods.

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