Panic Driving Behaviour in Non-Lane Based Heterogenous Traffic: Insights

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ABSTRACT
Natural disasters like fires, earthquakes, and other emergencies often cause panic-induced road driving behaviours. The situation gets complex in heterogeneous non-lane-based traffic coupled with non-motorized vehicles. This study, thus, concentrates on examining panic-induced driving behaviours, optimising key traffic parameters, and identifying effective traffic control strategies under the conditions mentioned above. This study focuses on three major intersections in Dhaka, the capital of Bangladesh, a country in Southeast Asia, incorporating route and vehicle dynamics. A sensitivity analysis was performed to optimise traffic parameters, while a comparison of manual police-dependent control systems and adaptive signals was conducted to find the optimal control strategy. The study analysed the impact of Car Following Model Parameters on key traffic performance metrics by calibrating the model to reflect the panic conditions. No significant difference was found between adaptive and manual signals during emergencies. Adaptive signals, however, initially create smaller queues and smoother traffic flow but degrade performance as traffic volume increases, leading to larger queues and reduced efficiency. The findings suggest that, though beneficial under normal conditions, adaptive signals become similar to police-dependent manned signals during emergencies. The insights will aid in developing optimal traffic management strategies to improve emergency evacuation efficiency in non-lane-based heterogeneous traffic environments, befitting developing and developed built-up urban areas.

Keywords: Panic Driving, Evacuation Route, Traffic Management, Simulation

INTRODUCTION

Sudden disastrous emergencies like fires or earthquakes, terrorist attacks, or public health crises can cause heightened stress and fear, leading to panic among road users. This panic-induced state often results in speeding, tailgating, and erratic driving manoeuvres, which can increase the incidence of panic-induced aggressive driving behaviour (*1*) as individuals prioritise their safety. Panicked drivers present a serious safety hazard to themselves and other road users. Evacuation routes can become congested, delaying emergency responses and stretching already limited resources, complicating disaster management and increasing the likelihood of additional injuries or fatalities. The situation becomes worse in areas where traffic is non-lane-based and heterogeneous, a common feature in less developed countries like Bangladesh (*2*). In these regions, various motorised vehicles—including buses, cars, CNGs (Compressed Natural Gas vehicles), and trucks and non-motorized vehicles (NMVs), such as rickshaws, bicycles, and pedestrians —share the same roadways. In a lane-based transport system, drivers can switch lanes and take advantage of gaps in traffic, potentially improving their ability to evacuate quickly and safely in an emergency. However, in non-lane-based traffic systems, such flexibility is not possible. Drivers cannot maneuver as efficiently due to the lack of defined lanes and the more chaotic traffic flow. This limitation, coupled with the heterogeneity of non-lane-based traffic where vehicles of various sizes and speeds share the road, exacerbates the situation, leading to greater congestion and further hindering effective emergency responses.

Traffic signal control strategies are essential in managing these unpredictable scenarios. Countries like the United States, the United Kingdom, and Australia use Adaptive Traffic Signal Control (ATSC), which adjusts signal timings based on real-time traffic conditions. The current body of literature explores emergency driving behaviour, focusing on sensitivity analysis in the context of developed countries (*3–5*). However, these studies fall short of fully representing the traffic dynamics of developing countries when addressing driving behaviour in emergencies. A full-scale exploration of panic driving behaviour, particularly across heterogeneous traffic, would aid in understanding the complex interactions and safety implications of diverse vehicle types and driving patterns, ultimately leading to more effective traffic management and safety strategies.

Based on the research gap identified, this study will delve into the following two objectives: 1) to determine the critical traffic parameters to optimise throughput considering a panic situation in the heterogeneous non-lane-based traffic of a built-up city; 2) to ascertain an appropriate traffic control mechanism for managing the above-mentioned aggressive driving. Thus, this study will provide valuable insights into important policy implications for emergency management which may be applicable even for built-up areas of a developed city.

LITERATURE REVIEW

Studies have consistently shown that driving behaviour under normal conditions differs significantly from behaviour in emergencies. These differences have been investigated (*6*), focusing on perception reaction time (PRT) and critical headway. Their findings indicate that PRT follows a normal distribution in normal and emergency situations. However, PRT is shorter during emergencies compared to normal conditions. Additionally, the study found that the critical headway—the minimum safe distance drivers maintain between vehicles—is also reduced in emergencies. Similarly, another study (*7*) observed that drivers' ability to manage their vehicles declines under stress or emergency conditions. This decline is attributed to delayed reaction times and decreased judging speed and distance accuracy. Given these variables, driving behaviour in emergencies shares similarities with aggressive driving. Such aggressive driving is typically characterised by speeding, tailgating, erratic lane changes, and disregarding traffic signals (*8*).

Numerous studies have explored aggressive driving behaviour across various contexts, employing diverse methodologies and models. In a recent study, authors identified and quantified aggressive driving patterns in the West Midlands, UK, using a GeoSpatial and Temporal Mapping of Urban Mobility (GeoSTMUM) approach with telematics data (*9*). The majority of the studies focused on modelling and analysing aggressive driving behaviour. For instance, few authors calibrated parameters to replicate aggressive driving behaviours at a roundabout using SSAM-derived time to collision values (*3*). In contrast, others conducted a sensitivity analysis of VISSIM driver behaviour parameters to understand the impact of vehicle aggressiveness on safety (*10*). Another author assessed crash potential under aggressive driving events on freeways using driving simulators and microscopic traffic simulation models (*11*). While these studies offer valuable insights into aggressive driving behaviour, they generally concentrate on general aggressive driving rather than panic-induced aggressive driving. This specific phenomenon remains underexplored in the existing literature. One study (5) examined the impact of driver aggressiveness in an emergency on evacuation effectiveness. Additionally, most research has focused on developed countries, which often feature less complex traffic compositions than developing countries where lane discipline may not be well-maintained.

Many authors used the Wiedemann 99 car following model for simulating erratic driving behaviour under various traffic scenarios. **Table 1** summarises the suggested/optimised values of such parameters in the existing literature under different traffic contexts mostly related to aggressive driving. Since there is a research gap in defining panic-induced driving, parameters commonly used to define aggressive driving could serve as a starting point for identifying similar behaviours in panic driving. A description of the parameters and the ranges of those parameters used in this study is given in **Table 1**. In this table, the following traffic contexts are mentioned:

Bottleneck condition: A bottleneck condition refers to areas on roadways where traffic flow is restricted, often leading to congestion and breakdown. These bottlenecks are typically caused by merging, aggressive lane-changing, or variations in speed

Safety analysis: safety analysis in a traffic context is a proactive approach that evaluates the risk of crashes using surrogate safety measures, such as traffic conflicts. Microsimulation models and advanced statistical techniques predict rare crash events based on more frequently observed traffic interactions.

Rear-end conflicts: This conflict is the most common accident type at signalized intersections, which occurs when a vehicle slows down while approaching or passing through an intersection, putting the vehicle behind it in a potentially dangerous situation.

Congested Traffic: A transport condition marked by slower speeds, longer travel times, and increased vehicle queues, typically occurring when traffic demand exceeds roadway capacity.

Normal (overtaking considered): Mixed traffic flow with abrupt lane changing, with slower heavy vehicles in inner lanes forcing risky overtaking.

In times of emergency, ensuring adequate protection through responsive traffic management techniques has become a primary concern for the traffic sector. Addressing this concern, numerous scholars have tried to develop methodologies or optimise signal strategies to plan and operate the evacuation process more effectively and efficiently. One study emphasised traffic signal timing optimisation under heterogeneous traffic conditions, concentrating on lane-based optimisation models (*12*). While primarily addressing normal traffic situations, their adaptive control strategies, capable of responding to real-time data, implicitly cover emergency scenarios on urban traffic networks, including arterial and collector roads.

Similarly, some authors investigated the effectiveness of control measures such as ramp metering and variable speed limits in preventing congestion and improving traffic flow on expressways (*13*). In another study, the authors focused on heterogeneous traffic conditions, addressing lane- and non-lane-based traffic dynamics (*14*). The study effectively identified and mitigated congestion by utilising a double-layer ramp-metering model, enhancing overall traffic flow efficiency on expressways. Despite such efforts, the existing studies often overlook the significant changes in driving behaviour during panic driving conditions among heterogeneous non-lane-based traffic. This study worked on that limitation focusing on heterogeneous non-lane-based traffic context.

TABLE 1: Wiedemann 99 parameter values in previous studies

Parameter	Default value	Suggested value/range in literature	Reference	Traffic context	Range used in this study
CC0 (Standstill distance)	1.5 m	0.5 to 2.5	*(10)*	Aggressive driving	0.2 to 2
			(15)	Bottleneck condition	
		0.5 to 1.5	*(16)*	Congested traffic	
		2.75	*(17)*	Safety analysis	
		0.59	*(18)*	Rear-end conflicts	
CC1 (Gap time distribution)	0.9 s	0.5 to 1	*(19)*	Congested traffic	0.5 or 0.9
		0.5 to 1.3	*(10)*	Aggressive driving	
		0.5	*(17)*	Aggressive driving	
			(20)	Safety analysis	
		0.5 to 0.9	*(16)*	Congested traffic	
		0.6	*(21)*	Aggressive driving	
		0.58	*(18)*	Rear-end conflicts	
		0.7 to 1.7	*(15)*	Bottleneck condition	
		0.52	*(11)*	Aggressive driving	
CC2 (‘Following’ distance oscillation)	4	2 to 6	*(10)*	Aggressive driving	2 to 8
		2.92	*(18)*	Rear-end conflicts	
		2 to 10	*(22)*	Normal (overtaking considered)	
		2 to 8	*(15)*	Bottleneck condition	
CC3 (Threshold for entering ‘Following’)	-8.00	-4 to -12	*(10)*	Aggressive driving	-10 to -4
		-4	*(11,20)*	Aggressive driving	
		-4 to -15	*(19)*	Congested traffic	
		-10 to -5	*(15)*	Bottleneck condition	
		-8.34	*(18)*	Rear-end conflicts	
		-11.5	*(17)*	Safety analysis	
CC4 (Negative speed difference)	-0.35	-0.1 to -1.5	*(10)*	Aggressive driving	-2 to -0.1
		-0.1 to -2	*(19)*	Congested traffic	
		-0.3	*(17)*	Safety analysis	
		-0.05 to -1.05	*(15)*	Bottleneck condition	
CC5 (Positive speed difference)	0.35	0.1 to 1.5	*(10)*	Aggressive driving	0.1 to 2
		0.1 to 2	*(19)*	Congested traffic	
		0.3	*(17)*	Safety analysis	
		0.05 to 1.05	*(15)*	Bottleneck condition	
CC6 (Distance dependency of oscillation)	11.44	4 to 20	*(10)*	Aggressive driving	2 to 20
		2 to 20	*(19)*	Congested traffic	
		9.21	*(18)*	Rear-end conflicts	
		0 to 20	*(15)*	Bottleneck condition	
CC7 (Oscillation acceleration)	0.25	0.15 to 0.4	*(10)*	Aggressive driving	0.1 to 2.5
		1.12	*(11)*	Aggressive driving	
		0.45	*(20)*	Aggressive driving	
		0.26	*(18)*	Rear-end conflicts	

Parameter	Default value	Suggested value/range in literature	Reference	Traffic context	Range used in this study
		0.1 to 2.1	*(15)*	Bottleneck condition	
CC8 (Acceleration from standstill)	3.50	2.5 to 4.5	*(10)*	Aggressive driving	0.5 to 3.5
		4	*(21)*	Aggressive driving	
		3.42	*(18)*	Rear-end conflicts	
		2 to 3.5	*(15)*	Bottleneck condition	
CC9 (Acceleration at 80 km/h)	1.5	0.8 to 2.2	*(10)*	Aggressive driving	0.5 to 2
		0.5 to 2	*(15)*	Bottleneck condition	

METHODOLOGY AND DATA

The study's methodology is fourfold: i) Network coding in microsimulation software, ii) Sensitivity analysis of parameters related to simulating panic behaviour, iii) Generation of emergency scenarios, and iv) Design of signal systems (both Static and Adaptive) to determine the most suitable signal for emergency conditions. A microsimulation platform, PTV VISSIM, is used to model three intersections of Dhaka City, which is the capital of Bangladesh, incorporating both route and vehicle dynamics. After calibrating the model, to impart emergency and panic driving, this study explores the effect of the Wiedemann 99 Car Following Model Parameters on key performance variables and chooses a suitable parameter set through sensitivity analysis. Finally, an evacuation scenario is developed by altering traffic routes and two types of signal control strategies, Static Signal & Adaptive Signal, are compared to determine the adequacy. The methodology of this study is showcased as a flowchart in **Figure 1**.

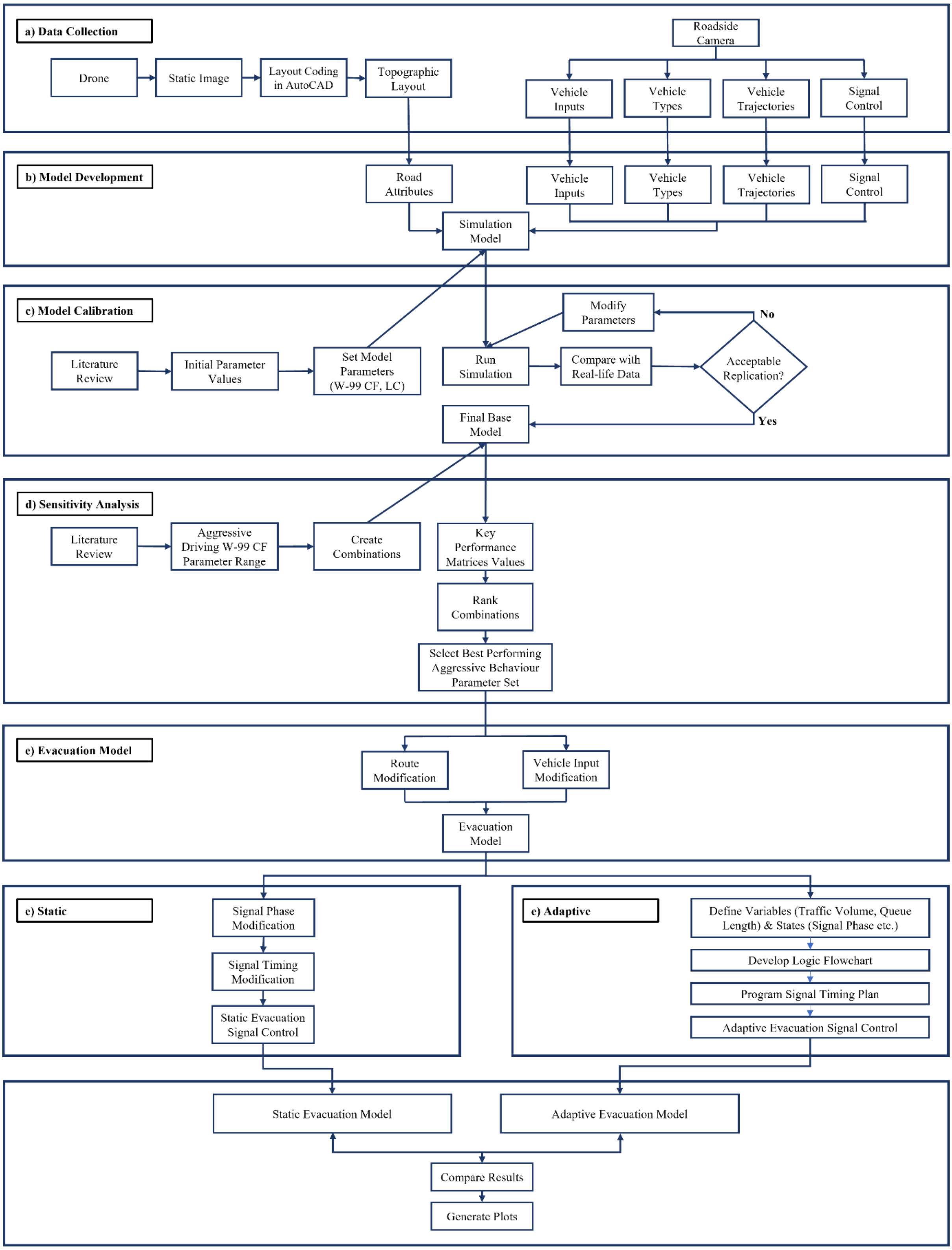

Figure 1 Methodology Flow Chart

Data Collection

The study area of this research consists of three intersections of the Dhaka City—Airport Signal, Bijoy Sarani Intersection, and Tejgaon Intersection. Airport Signal is a critical junction in Dhaka, connecting major roads and enabling significant traffic flow between the northern suburbs and the city centre. Bijoy Sarani, a major arterial route, intersects key roads and is strategically located near

significant landmarks, including the National Parliament House and the Prime Minister's Office. Moreover, the Tejgaon Intersection is also a critical traffic hub in Dhaka, situated in one of the city's most industrialised zones.
Figure 2 provides a Google Earth view of the study area and directions for traffic movement.

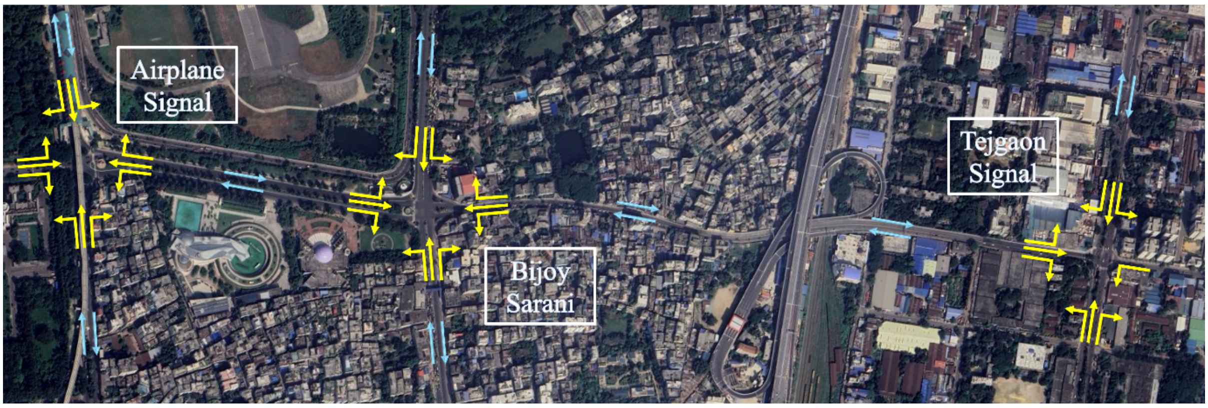

Figure 2: Google Earth View

A traffic video survey was conducted to ensure high-quality data collection of 12-directional traffic movements at these intersections. Video cameras with portable chargers and high-capacity memory cards were strategically placed to cover all four approaches of each intersection. Seven cameras per intersection were deployed to capture vehicle types and movement directions accurately. At the same time, drone footages were taken to plot topographical views of the study site which would be used for accurate network coding. For example, **Figure 3** illustrates the camera setup and locations at the Bijoy Sarani intersection. The field survey involved 24-hour video footage collected over a week, which included the total of each type of vehicle movement collected every 15 minutes and the signal details of each intersection. The peak hour was chosen for further analysis by consolidating every hour data of the 7 days and picking the hour which involved the most traffic movement. For this study, the peak hour was found to be on Sunday from 6 PM to 7 PM.

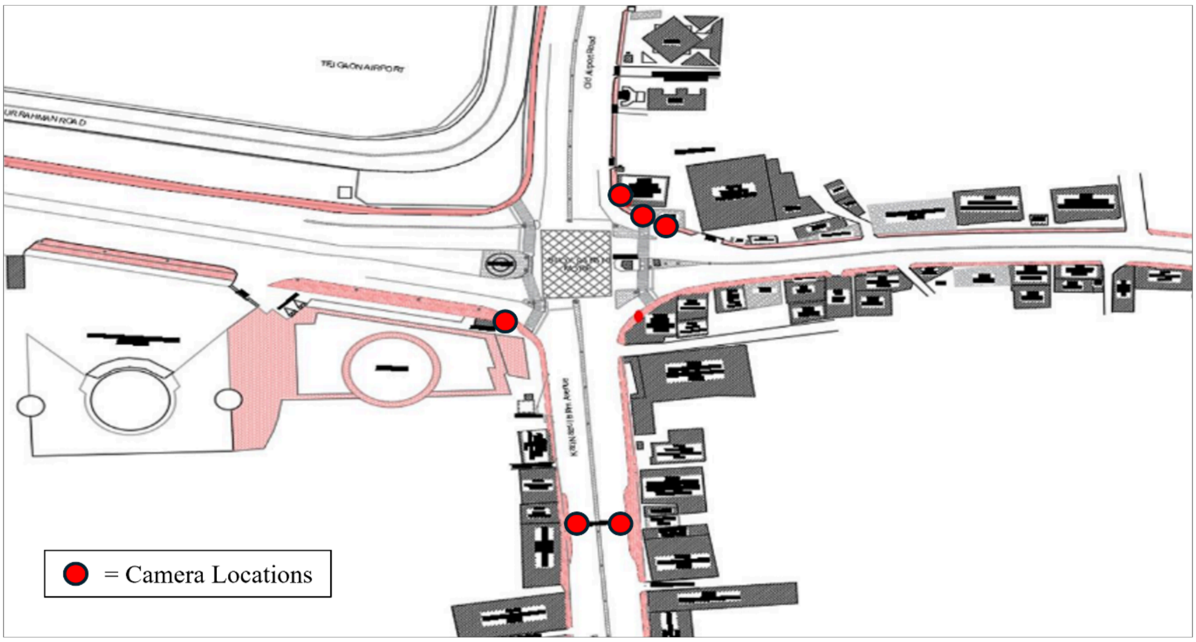

Figure 3 Topographic View of Bijoy Sarani with Camera Locations

Figure 4 showcases a viewpoint of one of the cameras placed at the Bijoy Sarani Intersection, and **Figure 5** presents a schematic diagram of the intersections, showing vehicle movement directions and peak hour traffic volumes. Observations indicated that private vehicles, including cars, motorcycles, and auto rickshaws/CNGs, dominated the traffic, comprising over 85% of vehicles. Private cars were the most prevalent mode, exceeding a 30% share on both weekdays and weekends. The share of auto rickshaws/CNGs and other non-motorized vehicles varied throughout the survey period. Furthermore, data on road geometry, such as lane counts and widths, was also collected for accurate model development.

Figure 4 Typical camera setup

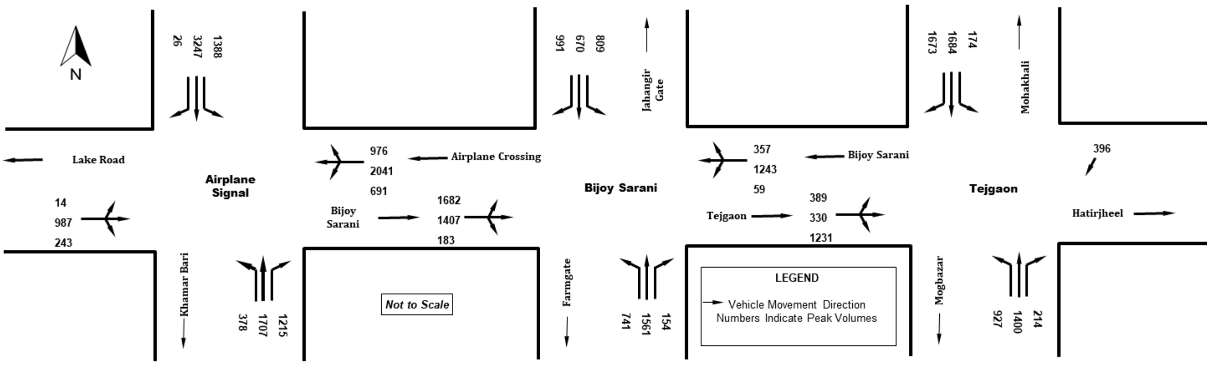

Figure 5: Schematic diagram of the three intersections

Microsimulation model development & Calibration

PTV VISSIM was chosen as the microsimulation platform in this study as it has been proven user-friendly and has better visual display capabilities (*23*). Additionally, it performs better than other simulating software in modelling complex road networks with traffic control and transit elements (*24*). To develop the microsimulation model, the VISSIM Graphic User Interface (GUI) was utilised to draw the whole network of the study area. The topographical data gathered from the surveys are input into the model as links and connectors, whereas signal heads and control were used to replicate the existing signals. Intermediate points were added to adjust the curves of the streets and data collection points were added on the road network for the calibration process. The calibration consisted of two major steps: (i) a Literature review of parameters for similar traffic networks (*25, 26*) and (ii) an Iteration of parameter combinations to find the best parameter set for calibration. After calibration, the model was validated using the GEH (Geoffrey E. Havers) statistic (*27,28*). GEH values under 5 typically indicate a good fit, but an acceptable value range for a non-lane-based heterogeneous traffic mix is up to 10. The traffic flow GEH value of 12 approaches in three intersections from five simulation runs varies from 6.1 to 8.92, which is acceptable. Furthermore, while comparing the observed and simulated data, the difference in queue length varied from 7.7 to 9.3%, representing the model's efficacy. **Figure 6** showcases the full simulation network used in this study.

Figure 6: Microsimulation Model

Sensitivity Analysis of VISSIM Driving Behaviour Parameters

Based on an extensive literature review, a range of car-following driving behaviour parameters to emulate aggressive behaviour during emergencies has been identified. The parameters, CC0-CC9, are classified into equidistant values for evaluation purposes. Except for CC1, which has only two logical values, all other parameters are divided into five equal intervals. These parameters are assessed based on four outputs: Average Headway Time (s), Average Headway Space (m), Average Speed (km/h), and Relative Delay (%). While the average speed of the vehicles in the simulation network and the relative delay can be directly obtained from VISSIM, average headway time and average headway space are calculated separately.

After obtaining the simulation outputs, this study employed a ranking system to achieve the desired aggressive driving parameter set for further analysis. In this system, parameters that yield the lowest values for Average Headway Time, Average Headway Space, and Relative Delay are assigned the highest rank, as lower values of these metrics indicate more aggressive driving behaviour. Conversely, the highest rank is assigned to the lowest value for Average Speed. When setting parameter values, one combination is tested while keeping the other parameters at their base model-calibrated values. Ranks for each output are calculated, and the combination of values with the lowest total rank is selected to represent aggressive behaviour during an emergency evacuation.

Generating Evacuation Scenario

The three intersections studied in this research are critically important in Dhaka as they connect between Dhaka South City Corporation (DSCC) and Dhaka North City Corporation (DNCC). In emergencies, this corridor connecting Airplane Signal and Tejgaon Signal is expected to function as a key evacuation corridor due to its placement along the borders of two city corporations. Under normal conditions, traffic flows in all directions along this route. However, for this study, it is assumed that an emergency has occurred in either one of the city corporations, necessitating the exclusive use of this route for evacuation.

To create an evacuation model, after calibrating the behavioural parameters to reflect aggressive driving, the traffic flow trajectories are adjusted to ensure that in simulation, all the vehicles are moving toward DNCC from DSCC. Additionally, it is assumed that due to a hypothetical emergency in DSCC, no traffic from DNCC is flowing in that direction. The traffic flow routes in this evacuation scenario are depicted in **Figure 7**. Consequently, the vehicle inputs and the routes that flowed traffic from DSCC to DNCC have been removed. It is important to note that no other physical attributes or traffic flow characteristics have been modified to aid the evacuation apart from the changes in driving behaviour parameters.

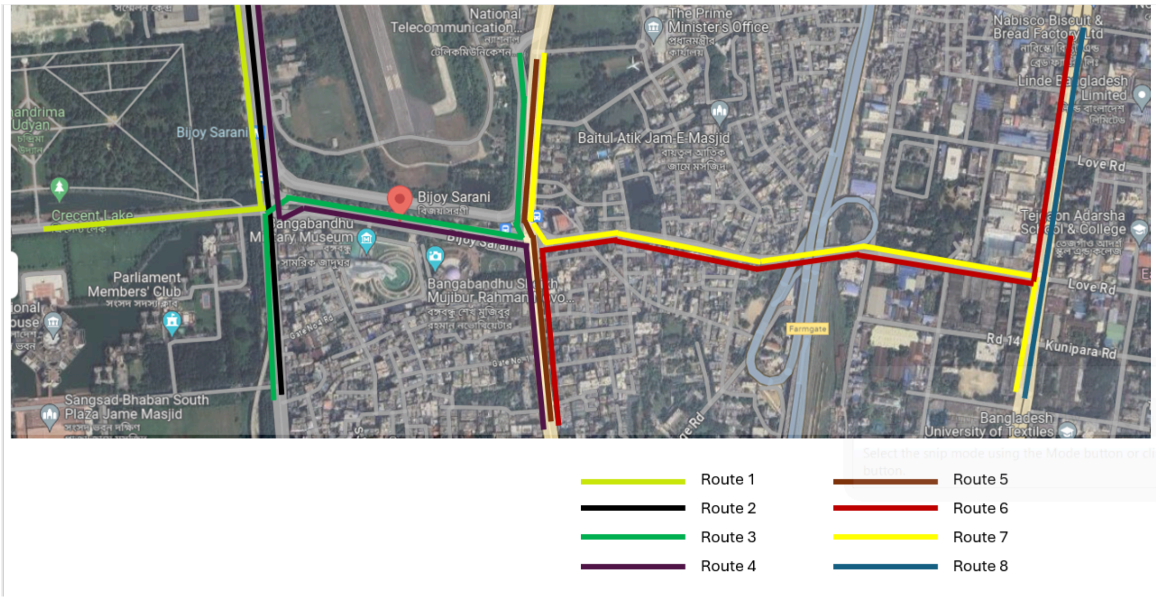

Figure 7 Vehicle Route considered for an emergency evacuation scenario

Signal Control Strategies

This study compares different signal control strategies to evaluate their performances in an evacuation scenario. For this comparative analysis, two types of suitable signalling systems are developed and implemented in the evacuation model- (i) Static Signal Control and (ii) Adaptive Signal Control. The performance of these signals was compared in terms of several performance metrics discussed on the next section.

Static Signal Control

A static signal typically consists of a fixed traffic control device with a predetermined pattern that does not change based on real-time traffic conditions. These signals operate on a set schedule with fixed intervals for red, yellow, and green lights. In Dhaka, most intersections are manually operated by traffic police. It is assumed that in an evacuation scenario, traffic police will adjust signal timings according to traffic movement. Since there is no definitive way to simulate manual traffic control in VISSIM, it is assumed that signal timings will change based on adjustments made by the traffic police. To implement this in the simulation model, the static signal timings are calculated according to changes in traffic flow movement in the evacuation model compared to the base model, with phases adjusted accordingly.

Adaptive Signal Control

Adaptive signal control is a dynamic traffic management approach that adjusts traffic signal timings in real-time based on current traffic conditions to optimise traffic flow and reduce congestion. In VISSIM, adaptive signals can be implemented using the VisVAP module, which facilitates the integration and simulation of various adaptive signal control strategies. This involves applying adaptive control algorithms that dynamically adjust signal timings and running simulations to evaluate and refine the system's performance for optimal traffic management. VisVAP is a tool within PTV Vissim that enables the development of signal control algorithms using object-oriented programming and flowcharts. It supports the simulation of programmable, vehicle-actuated signal controls by allowing users to create and implement logic programs.

VisVAP needs an ASCII database with a ".pua" extension, which includes details such as the number of phases, intergreen matrices, and signal plans. In this study, instead of using the CROSSIG add-on, a text editor is employed to create the ".pua" file, backed by previous studies (29,30). The control logic is crafted using the VAP (Vehicle Actuated Programming) language in VisVAP, and the resulting "*.VAP" file contains the adaptive control algorithm written in C++. For this research, three different intersections were considered, necessitating the creation of three distinct VAP files to simulate adaptive signals at each intersection. Each of these adaptive signal designs consisted of three phases, and a maximum green time was set to avoid excessively long green times due to persistent demands. These files are integrated into VISSIM, which manages the simulation according to the defined logic. The system connects traffic detectors and signals to the ".vap" files within the VISSIM environment to properly simulate the adaptive traffic control strategy.

RESULTS & DISCUSSION

Sensitivity analysis of car-following parameters

The study aimed to identify the most sensitive parameters in calibrating simulation models for aggressive driving. An analysis of the Wiedemann 99 model's car-following parameters was conducted to pinpoint those most significantly indicate aggressive driving behaviour. While the base model uses default values, the parameters were adjusted within specified ranges to simulate aggressive driving scenarios within the study context. These ranges, derived from existing literature, were divided into equal segments, referred to as parameter combinations.

The study measured four key metrics for each parameter combination, with their variations illustrated in **Figure 8**.

1. Average headway time (seconds) - Lower values suggest aggressive driving, as drivers follow other vehicles more closely.
2. Average headway space (meters)—Similar to headway time, lower values indicate a closer following, typical of aggressive driving.
3. Average speed (km/h) - Higher speeds indicate aggressive driving behaviour, as drivers generally maintain faster speeds.
4. Relative delay (%) - Lower delay values align with aggressive drivers' tendency to minimise travel time.

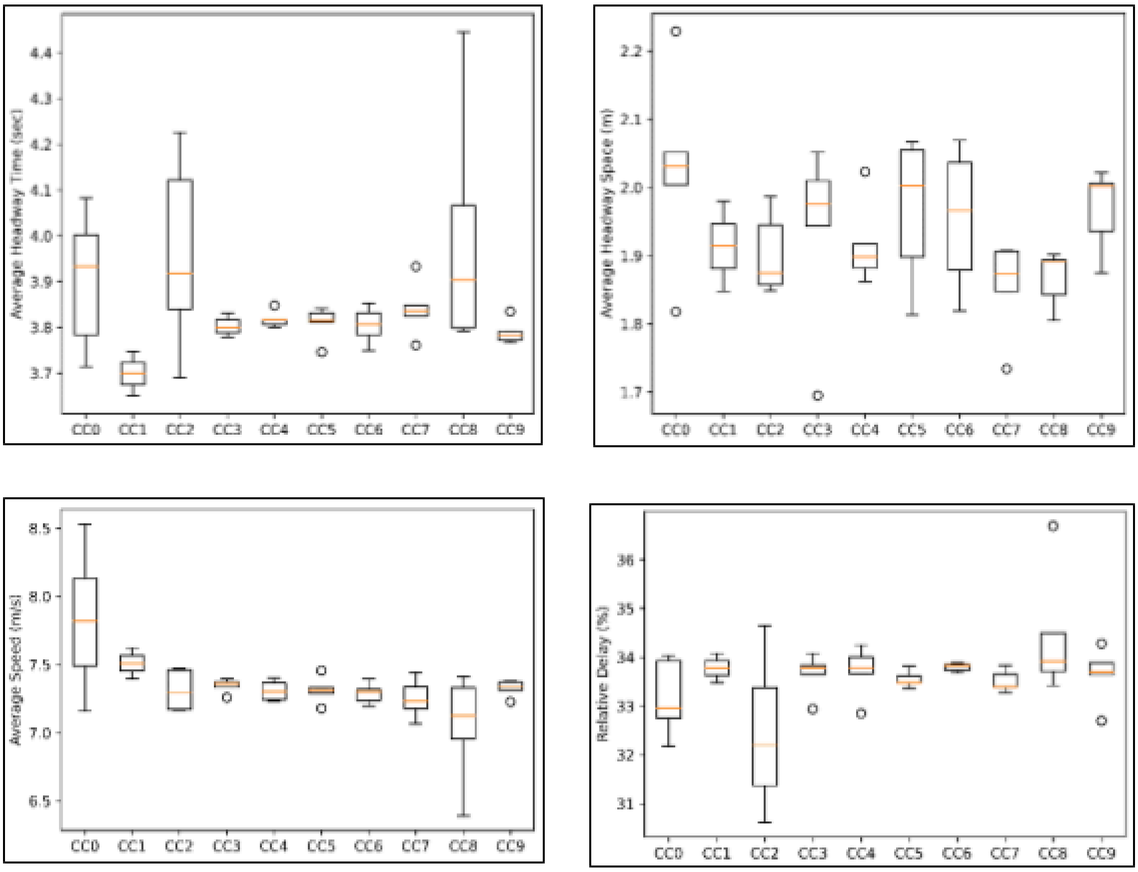

Figure 8: Metric Variation for Each Parameter

For certain ranges of the parameters CC0, CC2, and CC8, average headway time, average headway space, average speed, and relative delay were more variable. This increased variability, indicated by longer whiskers in the data, suggests a larger interquartile range (IQR). A larger IQR implies that the middle 50% of the data for these parameters is more spread out, indicating greater sensitivity in the traffic flow metrics output.

Each parameter combination, represented in Table 2, was then ranked based on these four metrics. The total rank for each combination was calculated by summing the ranks from all metrics. Combinations with the lowest total ranks were considered the most representative of aggressive driving behaviour, characterised by close following, higher speeds, and reduced delays.

TABLE 2: Parameter Optimization for Aggressive Driving Behaviour

Parameters	**Combinations**	**Average Headway Time (s)**		**Average Headway Space (m)**		**Average Speed (km/h)**		**Relative Delay (%)**		**Total Rank**	**Selected Value**
		Values	Rank	Values	Rank	Values	Rank	Values	Rank		
CC0	0.2	3.714	1	1.818	1	7.158	5	32.75	2	9	0.2
	0.65	3.783	2	2.031	3	7.492	4	34.03	5	14	
	1.1	3.933	3	2.004	2	7.821	3	32.95	3	11	
	1.55	4.002	4	2.052	4	8.133	2	33.93	4	14	
	2	4.083	5	2.229	5	8.532	1	32.17	1	12	
CC1	0.5	3.651	1	1.98	2	7.623	1	33.48	1	5	0.5
	0.9	3.748	2	1.848	1	7.397	2	34.08	2	7	
CC2	2	3.69	1	1.849	1	7.460	2	34.65	5	9	5
	3.5	3.839	2	1.875	3	7.300	3	33.38	4	12	
	5	3.918	3	1.858	2	7.472	1	31.37	2	8	
	6.5	4.122	4	1.987	5	7.172	4	32.20	3	16	
	8	4.226	5	1.945	4	7.168	5	30.62	1	15	
CC3	-10	3.779	1	2.052	5	7.397	1	33.78	1	8	-10
	-8.5	3.831	5	1.695	1	7.376	2	32.94	2	10	
	-7	3.788	2	2.01	4	7.360	3	33.83	4	13	
	-5.5	3.817	4	1.944	2	7.334	4	33.65	3	13	
	-4	3.8	3	1.976	3	7.259	5	34.08	5	16	
CC4	-2	3.816	3	1.898	3	7.400	1	32.85	1	8	-2
	-1.52	3.848	5	1.862	1	7.243	4	33.66	2	12	
	-1.05	3.8	1	2.023	5	7.304	3	33.79	3	12	
	-0.57	3.817	4	1.918	4	7.232	5	34.25	5	18	
	-0.1	3.807	2	1.882	2	7.365	2	34.00	4	10	
CC5	0.1	3.842	5	1.813	1	7.314	3	33.36	1	10	1.52
	0.57	3.831	4	2.003	3	7.180	5	33.82	5	17	
	1.05	3.812	2	2.067	5	7.291	4	33.48	3	14	
	1.52	3.746	1	1.898	2	7.456	1	33.61	4	8	
	2	3.815	3	2.055	4	7.333	2	33.47	2	11	
CC6	2	3.749	1	2.069	5	7.394	1	33.88	5	12	20
	6.5	3.783	2	1.819	1	7.300	3	33.85	4	10	
	11	3.853	5	2.037	4	7.237	4	33.83	3	16	
	15.5	3.832	4	1.966	3	7.194	5	33.73	2	14	

Parameters	Combinations	Average Headway Time (s)		Average Headway Space (m)		Average Speed (km/h)		Relative Delay (%)		Total Rank	Selected Value
		Values	Rank	Values	Rank	Values	Rank	Values	Rank		
	20	3.807	3	1.879	2	7.319	2	33.69	1	8	
CC7	0.1	3.761	1	1.906	4	7.445	1	33.40	2	8	0.1
	0.7	3.825	2	1.908	5	7.336	2	33.27	1	10	
	1.3	3.836	3	1.734	1	7.233	3	33.83	5	12	
	1.9	3.848	4	1.848	2	7.179	4	33.65	4	14	
	2.5	3.933	5	1.873	3	7.066	5	33.40	3	16	
CC8	0.5	4.445	5	1.843	2	6.393	5	36.69	5	17	3.5
	1.25	4.066	4	1.805	1	6.953	4	34.50	4	13	
	2	3.903	3	1.894	4	7.127	3	33.92	3	13	
	2.75	3.792	1	1.902	5	7.332	2	33.71	2	10	
	3.5	3.799	2	1.891	3	7.413	1	33.42	1	7	
CC9	0.5	3.791	4	1.936	2	7.313	4	33.70	3	13	1.25
	0.87	3.783	3	2.006	4	7.370	2	32.70	1	10	
	1.25	3.768	1	1.875	1	7.334	3	33.64	2	7	
	1.62	3.773	2	2.002	3	7.378	1	33.89	4	10	
	2	3.835	5	2.022	5	7.227	5	34.28	5	20	

The selected values are aligned with the context of the parameter to represent aggressive driving behaviour but do not create highly likely crash situations. The reasoning is given here-

1. CC0 (Average Standstill Distance): 0.2

   This value had the lowest overall rank, indicating it consistently resulted in the shortest headway times and distances. This behaviour is typical of aggressive driving, where the driver maintains minimal distance from the vehicle ahead. Aggressive drivers tend to stop closer to the vehicle in front, reducing the standstill distance. This tendency to follow more closely and reduce buffer space even when stopped can lead to a more compact vehicle arrangement at intersections and traffic signals

2. CC1 (Headway Time): 0.5

   This parameter also had the lowest overall rank. A low CC1 value suggests a short-desired headway time, which is characteristic of aggressive drivers who prefer to drive closer to the vehicle in front. These drivers favour shorter time gaps between vehicles, maintaining closer following distances. A lower CC1 value reflects this behaviour by allowing a smaller time gap between vehicles, increasing traffic density and flow and reducing reaction time.

3. CC2 (Following Variation): 5

   The value 5 had a relatively low overall rank, suggesting moderate following variation. This indicates that aggressive drivers are somewhat tolerant of speed changes in the vehicle ahead but maintain close following distances.

4. CC3 (Threshold for Entering "Following"): -10

   The lowest rank for this parameter indicates aggressive behaviour, as a very negative CC3 suggests that the driver starts following the leading vehicle even when the speed difference is significant. This parameter determines the gap time a driver accepts before following the vehicle ahead. A lower CC3 value means that drivers will accept shorter gaps, indicative of more aggressive driving behaviour where drivers follow more closely.

5. CC4 (Negative "Following" Threshold): -2

   A low CC4 value with a good total rank suggests aggressive drivers tend to decelerate later and less aggressively, indicating a tendency to maintain speed longer before braking.
6. CC5 (Positive "Following" Threshold): 1.52

   This value had a lower total rank, suggesting that aggressive drivers tend to accelerate more quickly when the gap with the vehicle ahead increases, indicative of a more aggressive acceleration profile. Aggressive drivers tend to drive faster. Increasing CC5, if it affects the desired speed or acceleration, would simulate this behaviour by allowing vehicles to reach and maintain higher speeds more quickly.
7. CC6 (Speed Dependency of Oscillation): 20

   The chosen value of 20 had the lowest total rank, indicating that aggressive drivers have less fluctuation in their following behaviour with speed changes and prefer steadier following gaps.
8. CC7 (Oscillation Acceleration): 0.1

   This value had the lowest total rank, suggesting that aggressive drivers tend to have minimal oscillation in their acceleration, maintaining a steady speed or quickly adjusting to changes in the speed of the vehicle ahead. CC7 represents the distance a driver is comfortable maintaining behind the vehicle in front, considering the driver's desired level of comfort and safety. Aggressive drivers tend to follow more closely, so a lower CC7 value reflects their preference for shorter following distances and more compact vehicle arrangements.
9. CC8 (Standstill Acceleration): 3.5

   The value 3.5 resulted in the lowest total rank, indicating aggressive drivers tend to accelerate quickly from a standstill, reflecting a preference for maintaining high speeds and reducing travel time.
10. CC9 (Acceleration at 80 km/h): 1.25

    This value was selected as it had the lowest total rank, suggesting that aggressive drivers have a high desired acceleration rate, which aligns with the aggressive driving characteristic of quickly reaching higher speeds.

These selected parameter values describe a driving style that prioritises short headways, quick accelerations, and minimal reaction times, all of which indicate aggressive driving behaviour.

Traffic Control Strategy Comparison

As mentioned in the methodology, two types of traffic control systems (static and adaptive) were evaluated in this study to find a suitable approach to tackle aggressive driving behaviour in emergencies. The assessment was done concerning the following parameters:

Performance Evaluation Concerning Average Speed

To assess which traffic control system would perform better in panic conditions, the average speed of the vehicles was compared in three different road types (four, three, and two-lane roads and link connectors) and three prime intersections of the study area. The analysis shows that in most cases, the adaptive signal system results in slightly higher average speeds than static signals, indicating that adaptive signals are more efficient in managing traffic flow (**Figure 9**). Particularly in connectors, this control strategy would be significantly more effective.

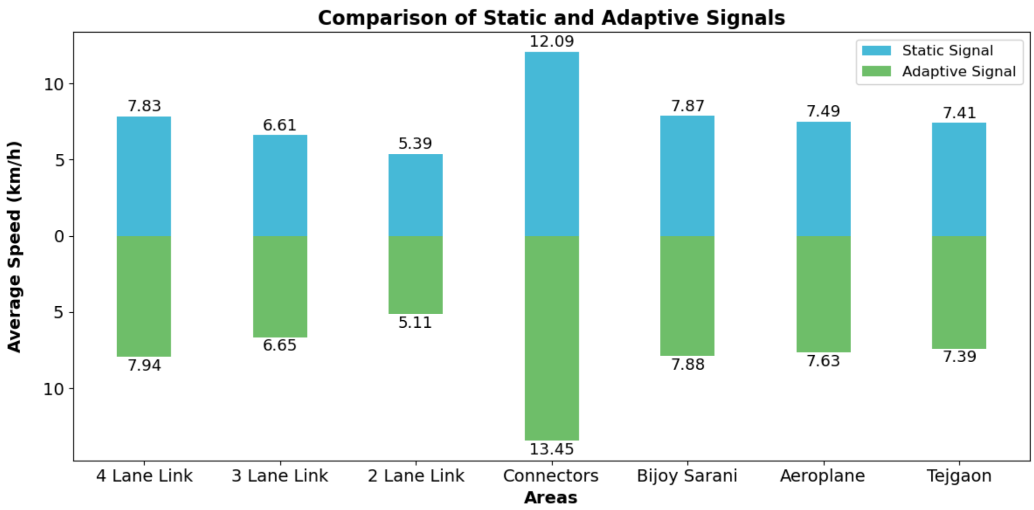

Figure 9 Comparison of Average Speed

Performance Evaluation Concerning Travel Time

Travel time was calculated for the eight routes (**Figure 10**) identified as crucial in an emergency. Due to their positional significance, these routes are expected to function as key evacuation corridors. The study discovers that, in most cases, the adaptive traffic control system could effectively shorten travel time. However, on some routes (Route 7, Route 5), the adaptive signals result in higher travel times, suggesting that the adaptive system might not be uniformly effective across all routes.

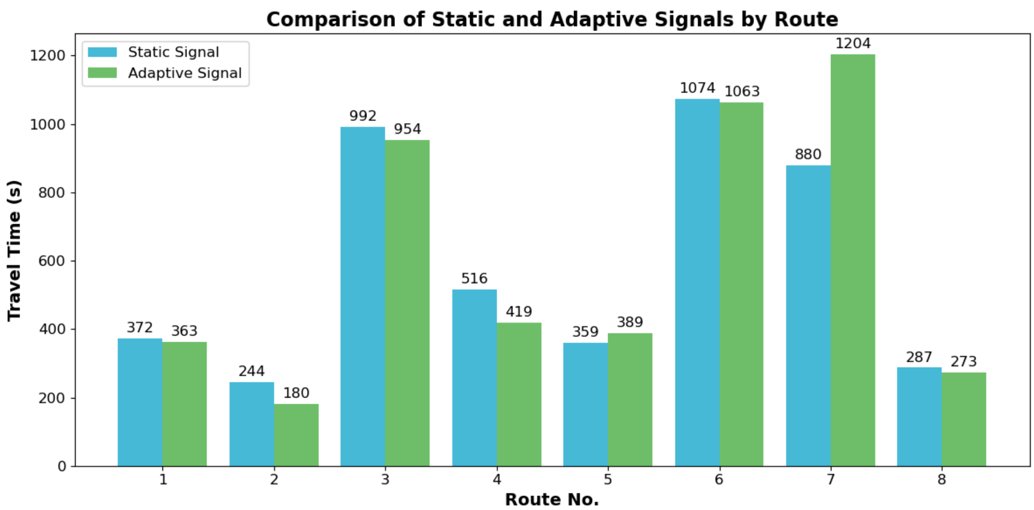

Figure 10: Comparison of Travel Time

Performance Evaluation Concerning Total Throughput Traffic

Another performance evaluation criterion for understanding the overall efficiency of the traffic signal control strategies was throughput traffic. The total throughput traffic is the number of vehicles successfully reaching the end of the simulation network, which, in this case, is reaching DNCC. According to **Figure 11**, in the first 5 minutes, both systems handle relatively the same traffic volume. However, with the passing time, the adaptive signal handles more vehicles in most time intervals, with a noticeable peak between 20-25 minutes, where the count reaches close to 900 vehicles. Both systems show similar vehicle counts between 31-35 and 41-45 minutes, indicating comparable performance during those periods. Overall, static signals tend to manage fewer vehicles compared to adaptive signals. The higher throughput under the adaptive signal indicates better traffic flow management, reduced congestion, and improved road capacity utilisation.

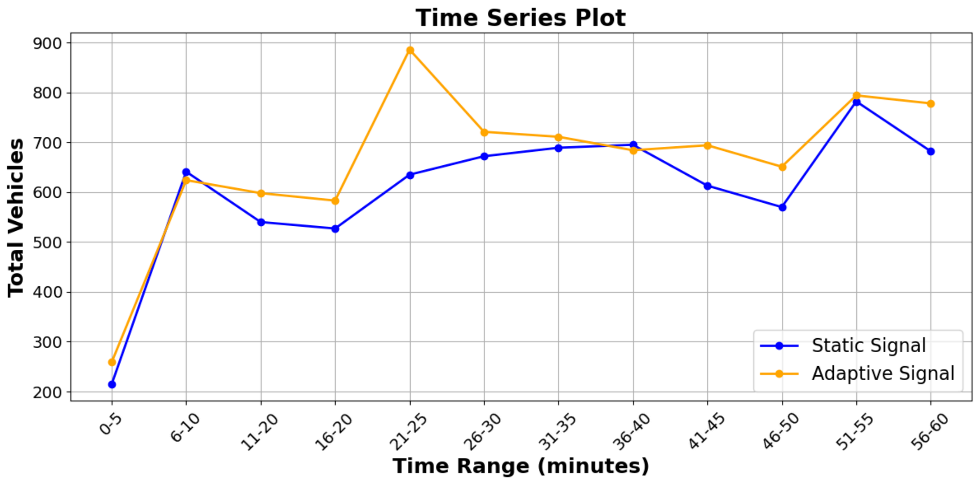

Figure 11: Time Series Plot for Total Throughput

Performance Evaluation Concerning Key Indicators of Aggressive Driving

The parameters used to define aggressive driving behaviour were assessed to evaluate static and adaptive signals. Additionally, three more parameters, Average Delay, Average Queue Length, and Level of Service, were considered for this assessment, with results summarised in a table. The results are presented in **Table 3**.

TABLE 3: Comparison of total volume count under static and adaptive signals

Performance Metric	Static Signal	Adaptive Signal
Headway Space (m)	1.8854738	2.0994673
Headway time (s)	3.487835	3.438997
Relative Delay	37.60%	34.34%
Average Delay	557.6514	519.3556
Average Queue Length (m)	71.439	66.167
Level of Service	F	F

Since lower headway space and headway time imply more aggressive behaviour, the table suggests that the adaptive signal shows a slight improvement in headway space (2.09m vs 1.89m) and headway time (3.44s vs 3.49s), which could potentially allow better management of aggressive behaviour. Though both signal types have a high relative delay (above 34%), the relative delay is slightly lower with adaptive signals (34.34%) compared to static signals (37.60%), which could indicate improved traffic flow efficiency. Regarding Average Delay and Queue Length, the adaptive signal reduces average delay (519s vs 558s) and queue length (66m vs 71m) compared to the static signal. Lastly, both signal types have a Level of Service of 'F', the worst possible rating, indicating failing traffic conditions with significant congestion and delays.

Overall Performance Comparison

Overall, the results suggest adaptive traffic signals may lead to slightly better traffic flow than static signals. There is a slight improvement in headway space and time, potentially reducing stop-and-go traffic. Additionally, the lower relative delay and queue lengths with adaptive signals indicate some improvement in traffic efficiency. However, it's important to note that both traffic signal types still resulted in significant congestion in this dataset. Thus, selecting a suitable traffic control system will depend on the situation and complexity of the traffic dynamics.

CONCLUSIONS

This study aimed to identify the sensitive traffic parameters of the Wiedemann 99 car-following model considering panic-induced aggressive driving behaviour and evaluate whether traffic police-controlled manual traffic management systems or adaptive signals perform better to manage such scenarios during emergencies in a non-lane-based heterogeneous condition. VISSIM was calibrated and validated to do the simulation part. Wiedemann 99 car-following model parameters' ranges were adopted from existing literature, and combinations were tested to understand the sensitivity of these parameters in an emergency context. The output performance metrics revealed that CC0. CC2 and CC8 were more sensitive to forceful driving than other parameters. This study then developed an evacuation scenario and tested static and adaptive signals to compare the suitability of the signals. The results showed that adaptive signals initially performed better, effectively handling the varying traffic conditions. However, as traffic volume increased and roads became saturated, the adaptive signals' performance declined, ultimately behaving similarly to static signals due to the formation of large queues. This indicates that while adaptive signals have potential, their effectiveness is limited under extreme traffic conditions. During Bangladesh's first Strategic Transport Plan (STP) in 2005, the v/c ratio of Dhaka was found to be 1.2. With little capacity enrichment and an increase in vehicle registration, the *v/c* of Dhaka is predicted to be manifold in 2024. Therefore, this study suggests that to tackle emergency traffic scenarios in such conditions, it may not be wise to always depend on adaptive traffic systems. The manual traffic control maintained by traffic police may better manage traffic flow in critical situations. This approach applies particularly to developing countries where lane discipline is often not followed, and traffic consists of heterogeneous travel modes.

The framework developed in this study is highly adaptable. It can be easily applied to various intersection types and traffic scenarios, making it a valuable tool for traffic management research and applications. Further research directives should concentrate on more extensive testing across different intersection types and scenarios to validate and refine the findings.

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AUTHOR CONTRIBUTIONS

Study conception and design: Md Asif Raihan, Ifratul Hoque; data collection: AFM Saiful Amin, Ifratul Hoque; analysis and interpretation of results: Ifratul Hoque; draft manuscript preparation: Ifratul Hoque, Madeha Sattar Khan, Maria Mehrin, Mushirah Tasnim, Sadia Tahsin Quadir, Sadia Afrin Aiswarza, Md Asif Raihan. All authors reviewed the results and approved the final version of the manuscript.

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