Simulated Conflict Based Safety Evaluation Models for Hetergenous Traffic in Controlled Intersections

Nayeem Islam[1], Md. Omar Faruk[2]

[1]Department of Civil Engineering,
Bangabandhu Sheikh Mujibur Rahman Science and Technology University, Gopalganj, Bangladesh
nayeemislam@bsmrstu.edu.bd

[2]Consulting Engineer
Tallahassee Metropolitan Area, Florida, USA
omar211faruk@gmail.com

Abstract*: *In this paper, an attempt is made to investigate how traffic conflicts identified from microsimulation models can be correlated with explanatory variables which have been traditionally used in accident prediction models. In developing countries with heterogenous traffic streams, availability of accident data is limited especially since accidents are rare events. Such traffic streams normally have some unique attributes like absence of lane discipline, presence of non-motorized vehicles. In urban intersections with such slow-moving traffic streams, conflicts are more useful determinants of intersection safety rather than previous records of accidents since geometry of intersection may be changed from the time to time. Simulated conflict-based safety evaluation models were developed for intersections of Dhaka city. The intersections were modeled in VISSIM after suitable calibration, for 8 hours of peak hour traffic. Surrogate Safety Assessment Model (SSAM) was used to identify the corresponding simulated hourly conflicts from the resulting trajectory files. It was found that hourly simulated conflicts had a significant statistical relationship with observed hourly traffic volume entering the intersection from major and minor roads. Increasing volumes of non-motorized traffic was found to contribute to intersection safety.

***Keywords*: conflict, surrogate safety measures, micro-simulation, heterogeneous traffic**

(Article history: Received: 30th October2021 and accepted 21st December 2021)

I. Introduction

Roadway environment, traffic and human dimensions are integrated in the concept of roadway safety and actively participate in any safety situation. For any particular roadway network, the safety performance explicitly and implicitly hinges upon the traffic behavior, geometric feature of the junctions, which implies that lack of control over the dimensions of traffic safety acts as a deterrent to the safety and mobility of road users at the intersections. The fact that intersections are more susceptible to the safety concern is due to the nature of traffic movement, which results from a variety of angular, left or right turning actions. A typical junction following left hand driving convention with four approach roads handles 12 movements of traffic from different approaches among which 4 right turning movements are critical in terms of safety and roadway design. However, apart from the critical movements, junctions have always been in the limelight for roadway safety issues for facilitating complex interactions among distinctive factors. Reference [1] denoted a number of traffic and geometric factors that contribute to the road safety issue, such as driver features and conditions (experience, stress, tiredness, etc.), road characteristics (type of road, road surface, geometric features, etc.), traffic conditions (volume, speed, density, etc.), vehicle attributes (maneuverability, braking capability, stability, etc.), and environment (weather conditions, light conditions, etc.). The control and constrains over the factors retards the critical issues promoting safety concern. Moreover, proper evaluation and understanding of the existing condition of safety is necessary to prioritize warranted measures at specified locations. Following this essence to develop an efficacious countermeasure with a goal to arrest conflicting situations, assessment of existing practice is warranted and this is where safety assessment models come into play. These models are convenient devices for evaluating road safety conditions on the basis of objective parameters derivable from vehicle motion characteristics.

Recently researchers have preferred simulated traffic conflicts for safety evaluation purposes [2] [3]. According to the definition by reference [4] traffic conflict is "an observable situation in which two or more road users approach each other in space and time for such an extent that there is a risk of collision if their movements remain unchanged" . The assumption is that conflicts would have led to accidents had not evasive maneuvers been taken by road users and thus conflicts are close representations of accident situations. Conflict analysis is useful in safety evaluations when sufficient crash data is not available for the intersections under consideration. Also since conflicts occur more frequently compared to accidents, they are more suitable for being used in statistical models for safety assessment. For objective determination of traffic conflicts, conflicts are identified using threshold values of proximal safety indicators, which mathematically express temporal and spatial proximity characteristics of conflicts. The most widely cited proximal safety indicators in literature are: time to collision (TTC) and post-encroachment time (PET). Time to collision, may be defined as the time for two vehicles to collide if they maintain their current speed and trajectory. TTC has a finite value only if two vehicles are on a collision course and this value decreases with time. PET is defined as the temporal difference between the occupancy of the same spatial point or area by two vehicles. Reasonable estimates of TTC and PET can be attained from vehicle tracking system, video image processing algorithm, loop detectors or manual frame by frame analysis of recorded video data by trained observers.

Identification of simulated conflicts from microsimulation models has been expedited by development of Surrogate Safety Assessment Model (SSAM) by Federal Highway Administration (FHWA). SSAM identifies simulated conflicts

Many cities in developing countries like Dhaka have heterogeneous traffic streams where eclectic mixes of motorized and non motorized modes share the same roadway space. Consequently there is a great divergence in the static and dynamic characteristics of different modes using the same carriageway resulting in some unique characteristics of heterogeneous traffic stream.

Some of the unique attributes of heterogenous traffic streams are:

1. Absence of lane discipline
2. Significant presence of non motorized vehicles
3. Presence of vehicles of different widths
4. Absence of any concept of car following
5. Development of queues which grow both longitudinally as well as laterally

For the purpose of this study 6 major intersections of Dhaka city has been incorporated as a case study. Dhaka has a heterogeneous traffic stream composed of significant numbers of non-motorized vehicles called rickshaws. Although major intersections in Dhaka handle large volumes of traffic during peak hours and are equipped with signal filters, the drivers respond to the gesture of the traffic police rather than traffic signals. In addition, geometry of the intersections along any corridor differs markedly from one to another. Some of these intersections handle large volumes of non-motorized traffic during peak hours while others oversee little non-motorized traffic during the same duration. Most citizens are reliant on road transportation so safety on roads is still a major concern for Dhaka.

Thus it is necessary to develop a feasible safety evaluation tool for major intersections of Dhaka city. Therefore the objective of this paper is to establish relationship between conflicts and traditional explanatory variables in accident prediction models: volume of traffic entering intersection from major and minor roads and volume of NMV entering intersection.

II. SAFETY ASSESSMENT

Traffic safety assessment is challenging and complex in process due to the infrequent nature and uniqueness of the crashes. In short, traditional safety evaluation methods cannot be undertaken without a considerable record of crash data. Given the limitation over the availability and information quality of crash incidences, surrogate safety measurements (SSMs) are used for safety assessment. Federal Highway Administration (FHWA) developed a software package called the Surrogate Safety Assessment Model (SSAM) to estimate conflicts based on microscopic simulation. It was developed to automate the process of traffic conflicts analysis using microscopic traffic simulation models. The SSAM operates through several algorithms to identify conflicts from vehicle trajectory files generated by microscopic simulation models, such as the VISSIM, PARAMICS, AIMSUN and TEXAS. The outputs of SSAM include the number, the type, the severity, and the locations of simulated conflicts. Five surrogate safety measures have been used in SSAM to evaluate the severity of a simulated conflict, which are the time to collision (TTC), the post encroachment time (PET), the deceleration rate (DR), the maximum speed (MaxS) and the speed differential (DeltaS). Rear-end, lane-change and crossing conflicts are the three distinct types of simulated conflicts considered in the model. A conflict is recorded in the software when the minimum TTC and PET indicator values surpass the predefined threshold values, and the conflict type associated with each conflict is distinguished according to the lane and link information or the angle between the two converging vehicles. These identified surrogate safety measures provide necessary information for the much desired proactive evaluation of road safety [5].

Several researchers have contributed to evaluate the feasibility of SSAM in predicting crashes through microscopic-simulation. Reference [6] advanced a linear regression model to compare simulated and observed field conflicts to evaluate the accuracy of the joint force of SSAM and VISSIM . The orchestrated study found that SSAM is apt to provide acceptable results for rear-end conflicts with the mean average percentage error (MAPE) value of 16%. However, the results of lane-changing and crossing conflicts are only moderately acceptable with higher mean average percentage error (MAPE) values of 79% and 24% respectively. Reference [7] searched for the potential to calibrate and validate the microscopic traffic simulation models by drawing a comparison between simulated and field data. Reference [7] have utilized the Crash potential Index (CPI) to estimate safety performance of signalized intersections in terms of rear end crashes. They compared to the observed conflicts from the NGSIM field-collected vehicle trajectories using a deceleration rate to avoid the crash (DRAC) and a crash potential index (CPI), to validate the simulated model for safety evaluation. The study showed that the calibrated traffic simulation model reflected the realistic safety performance measures (field data) as the simulated conflicts and the observed conflicts matched within the 95% confidence interval.

Reference [8] and Reference [9] investigated the potential of simulated conflicts as key variables in crash prediction models. Reference [9] tried to prove the potential of microscopic traffic simulation models for assessing surrogate safety at urban un-signalized intersections by comparing traffic crashes occurred and traffic conflicts estimated from the AIMSUN traffic simulation software and SSAM. In this case, three different regression models were developed using 5-year crash data, the number of conflicts estimated from the simulation runs, and peak hour volumes on major/minor roads, as follows: (1) traffic volume-based model, (2) traffic conflict-based model, and (3) traffic volume and conflict-based model. As a result, the traffic conflicts-based model provided the best performance in terms of the goodness-of-fit test (i.e., 0.967R value and the p-value of conflict variable less than 0.05) over the traffic volume-based models. Reference [8] compared the explanatory power of simulated conflicts derived from two different simulation models by SSAM analysis, in crash prediction models for 4 legged signalized intersections. VISSIM simulation model was used with precalibrated parameter values while for the Paramics model, considerable effort was expended to estimate parameters endogenously. The resulting crash prediction models both had simulated conflicts as the statistically significant explanatory variable with very similar coefficient estimates for the variable (0.3461 and 0.3892) in both models. However, the VISSIM simulated conflict based crash prediction model was found to have poor explanatory power for predicting crashes at intersections with relatively low and high entering traffic volumes.

As for other contributions, Reference [10] proposed new simulation-based surrogate safety measures with two parameters, as follows: (a) a modified time to collision (MTTC), derived from time to collision (TTC), relative speed, and acceleration rates between leading and following vehicles; and (b) a crash index (CI), developed to incorporate a crash severity factor for the MTTC. This study showed that the simulated MTTC and CI values are important to estimate potential traffic conflicts because the correlation values between the actual accident data and the simulated MTTC and CI are 0.92 and 0.91, respectively. Reference [11] evaluated different traffic signal treatments (i.e., amber time extension, dilemma zone green extension, and all-red extension) at signalized intersections for the purpose of safety estimation. VISSIM was used to extract vehicle trajectories and the number of red light violations, and the post encroachment time (PET) were used as surrogate safety measures. Reference [12] applied VISSIM to model the active traffic management (ATM) strategies including variable speed limit (VSL) and peak-period shoulder use, and evaluated the safety benefits of these strategies using SSAM. Similarly, Reference [13] used the combination of VISSIM and SSAM to quantify the potential crash risk of aggressive driving on the roadways..

So far the available microscopic traffic simulation models were commonly used to compute safety surrogate measures such as TTC, PET, and MTTC, which are the basis of identifying traffic conflicts.

All the literature tried to validate the simulated traffic conflicts by drawing contrast to the field crash data and showed that there exist a significant relationship between traffic conflicts and crashes, depicting traffic conflicts as a representative estimator of surrogate safety. However, much of the research has been carried out in cities with homogenous traffic streams maintaining good lane discipline. By contrast, the present work tries to find whether a definitive relationship between exists between conflicts identified from simulation models to observed traffic volumes in intersections which have an unique heterogeneous traffic streams. An additional objective of this paper is to determine the effects of non motorized vehicles on the safety situations at these intersections.

III. METHODOLOGY

For the purpose of this study, traffic volume and geometric data of the six signalized intersections were collected from the field. The selected intersections should satisfy the following criteria: (a) Intersections should be among the most accident prone intersections of Dhaka city as per records of accidents by local authorities; (b) Three intersections should have low volume of non-motorized traffic, resulting from the ban of rickshaws from major approaches; (c) Three intersections should have high volumes of non-motorized traffic. This criteria's enable the authors to investigate the effects of non-motorized traffic on safety at signalized intersections.

Traffic volumes were observed at the intersections during weekdays and weekends. It was found that higher traffic volumes occurred at specific periods of time during the day. Specifically, two 4 hour time intervals were observed, one in the morning (8:00 AM to 12:00 PM) and another during the afternoon (4:00 PM to 8:00 PM). Researchers have often attributed higher traffic volumes to be a cause of accidents. It can also be perceived that in mixed traffic situation where lane discipline is absent, higher traffic volumes result in drivers making more accident prone maneuvers since the movement of vehicles is severely constrained. The objective of this study is to investigate safety of road users in situations, where safety is likely to be compromised much more than other times. Thus the above mentioned peak time periods of the day were investigated in this study.

The geometric and traffic data required for calibration, validation of the simulation model at these intersections included: road width, total traffic volumes in each road, classified traffic volumes involved in each turning movement for each vehicle type, information on maneuvers receiving priority in conflict situations. Video cameras were installed at suitable locations over the study intersections and recorded at 4 periods of 15 minute interval for every hour of the 8 hour time period under investigation. The relevant traffic data was extracted from the recorded video for each intersection.

It is a fact that microscopic-simulation models are quite sensitive to traffic signal phasing times at intersections. It was previously mentioned that signalized intersections in Dhaka are operated by gestures of traffic police rather than change in color of signal lights. So signal timings corresponded to the time traffic police stationed at the intersections would provide for discharge of vehicles from a particular road. Considering average phase time and phase sequence in field condition at peak and off-peak periods 20 cycles were recorded to determine the phase timing for each of the approach of the six intersections. As operational parameters, these phase time and cycle time was assigned in the microscopic simulation model during calibration phase.

IV. MICROSCOPIC SIMULATION MODEL CALIBRATION

For the purpose of this study 6 intersections of Dhaka city were simulated in VISSIM. The data used for calibration of VISSIM model of the six intersections were retrieved from video data of the six intersections. These data were collected on 4 to 6 March 2012. This study follows the calibration guidelines provided by [14] for non-lane based heterogeneous traffic at signalized intersections. This was done since the traffic operation covered in the study by Reference [14] resembles the conditions at the six intersections covered in this study. In order to ensure an accurate representation of real life traffic operation, both system and operational calibration was conducted.

In this study the intersections were modelled as isolated systems. Traffic demand input was given in the VISSIM model of each intersection based on the traffic count data recorded at the critical locations of different links in the intersection. Traffic composition for the different approaches in each intersection was created according to the record of the classified vehicle count data. The classified directional vehicle count data was used to provide routing decisions in all the links of the intersection to ensure simulated directional flow of different vehicle categories match with field measurements. This is a particularly important since the influence of the proportion of non-motorized vehicles participating in right turning manoeuvres on intersection safety will be investigated in this study. Signal control was implemented in VISSIM according to the signal timings obtained in the field. Eight types of vehicle were created to replicate traffic composition of the study intersections such as: (1) Rickshaw; (2) CNG; (3) Leguna; (4) Bicycle; (5) Bike; (6) Car; (7) HGV; (8) Bus. Local vehicles were modelled in 3D Studio-Max first and then converted into recognizable vehicle element of the microscopic simulator as presented in Fig. 1. The simulation warm-up period was 30 minutes. Vehicles were calibrated for the desired speed distribution, acceleration, and deceleration as well as for the physical dimension as presented in Table I.

To replicate the prevalent non lane based driving behaviour in the intersections of Dhaka city, a customized link behaviour type was defined. The driving behaviour parameter sets for the default link were changed to match the non-lane based driving behaviour seen in the field. The minimum lateral distance for all vehicle classes was changed to 0.30 m at 0 km/h and 0.42 m at 50 km/h. Overtaking was permitted on the left and right sides of the same lane. The car following and lane changing parameters were also modified to fully represent the driving the behaviour seen in the field. All the modified driving behaviour parameters are listed in Table II.

The modified values of these parameters indeed adjusted the observed intersection capacity which markedly differed from field measurements when default driving behaviour parameter sets were used. For modelling the six intersections the Wiedmann 74 model was used since it is mainly suitable for modelling urban traffic conditions according to the information in VISSIM user manual [15].

This study adopts the Geoffrey E. Heavers (GEH) statistic to compare field traffic volumes with those obtained from the intersection base model. As a general guideline, for model validation, GEH values less than 5 represents good model fitness. The computed GEH values for all hours of simulation run were obtained below 5, representing good level of conformity between the simulated peak hourly volumes and those measured in the field.

$$\text{GEH} = \sqrt{\frac{(\text{Simulated Flow-Observed Flow})^2}{0.5(\text{Simulated Flow+Observed Flow})}}$$

V. SSAM ANALYSIS

Trajectory files from each simulation run were extracted from the simulation model. This trajectory data was analyzed by SSAM (version 2.1.6). Analysis of trajectory data is initiated in SSAM upon specifying threshold values of TTC, PET and conflicts angles. The threshold value of TTC and PET used were 1.5 s and 5 s respectively. This is suggested in previous research [16] and used by recent studies [8-9]. However, according to literature, researchers have not agreed on a unanimous classification of conflicts by conflict angle. Hence the present study will only consider total number of conflicts per hour for modeling purposes. For the purpose of starting the analysis, conflict angles are specified for different conflict types according to [5]. SSAM identified all critical conflicts for which 0<=TTC<1.5s and 0<=PET<5s. From this output, conflicts having TTC=0 or PET=0 were filtered out, since this is attributed to be imperfections associated with existing microscopic simulation packages. Also conflicts occurring during the warm up period of simulation run were filtered out from the final result.

An analysis of simulated hourly conflicts revealed rear end conflicts as the dominant form of conflicts at all intersections during the peak period. A much higher number of conflicts were observed at intersections having high volumes of non-motorized traffic compared to intersections with low volumes of non-motorized traffic which conforms to the finding that the presence of only a few non-motorized modes is enough to cause conflicts between motorized vehicles and on-road non-motorized vehicles [17]. This can be justified since non-motorized traffic has markedly different dynamic and static characteristics compared to motorized traffic. These characteristics generate a speed differential, which eventually lead to collision.

VI. STATISTICAL MODELLING

Multivariate analysis is by far most widely used analysis technique employed by researchers to develop crash prediction models. The earlier crash prediction models developed by multivariate analysis used multiple linear regressions. However, crash prediction models are essentially count data models and are best developed using the techniques of generalized linear regression which employ different discrete distributions like the Poisson distribution and Negative Binomial distribution. During the last decade, Negative Binomial model has been heavily favoured by researchers over the Poisson model due to its ability to accommodate over-dispersion since crash data has been found to be over-dispersed in many different studies.

In this study generalized linear models utilizing Negative Binomial distributions will be used to develop models to explain correlation between simulated conflicts and traffic volume entering an intersection. If Y_i is the number of simulated conflicts that occurred at the i-th peak hour time of the intersection under consideration, then it was assumed that Yi is a random variable with the negative binomial probability law. Then the negative binomial model can be written for each observation i as

$$\lambda_i = e^{(\beta X_i - \varepsilon_i)} \quad (1)$$

Where $\lambda_i = E\{Y_i\}$;

X_i = vector of explanatory variables;

β = vector of estimable parameters;

φ = over-dispersion parameter;

$$\mathrm{Var}\{Y_i\} = \lambda_i (1 + \lambda_i / \varphi) \quad (2)$$

e^{ε_i} is a gamma-distributed error term with mean 1 and variance φ^2

Maximum likelihood estimates for both β and ϕ were computed using the glm.nb() function from the MASS package in R 3.1.2.

A. *Model Evaluation*

Model evaluation is initiated by examining the statistical significance of the estimated regression coefficients (β) for each covariate in the model under consideration. In this paper, the p-values from the Wald test statistic will be used to assess the significance of the coefficients of the covariates in the model. The p-values are for the null hypotheses that β is not significantly different than 0. Incidence rate ratios (IRR) (exp(β)) were also calculated in order to allow further interpretation of covariates in each model. According to the reference [18] if the magnitude of IRR of a covariate is much larger than 1, then an increment in the value of that covariate is associated to a significant decline in safety at the intersection (either through an increase in number of crashes or conflicts in this paper). On the other hand, if the magnitude of IRR of a covariate is much smaller than 1, then an increment in the value of that covariate is associated to a significant enhancement of safety at the intersection. But unless the IRR is significantly different than 1, there is no change in the intersection safety situation.

In order to assess the explanatory and predictive power of each model, four goodness-of-fit measures has been be used. These include scaled deviance measure, Pearson chi-squared statistic, and *Akaike Information Criterion (AIC).*

These will be described briefly in following sections.

B. *Goodness of Fit Tests*

The likelihood ratio is ratio of the log likelihood maximized under the current model to the log likelihood of the saturated model. The scaled deviance of a model is equal to -2 times the log likelihood ratio. The scaled deviance (SD) for negative binomial models will be calculated as

$$SD = 2\sum_{i=1}^{n}[y_i \log(\frac{y_i}{\lambda i}) - (y_i + \varphi)\log(\frac{y_i + \varphi}{\lambda i + \varphi})]$$

The Pearson chi-squared statistic is computed by $X = \sum_{i=1}^{n} \frac{(y_i - \lambda i)^2}{\lambda i (1 + \lambda i / \varphi)}$.

Both the Scaled Deviance and Pearson chi-squared statistic is supposed to be chi-squared distributed with degrees of freedom equal to n-k-1.

Akaike information criterion (AIC) is a statistical measure that is used to discriminate between models having different number of parameters. Generally models with a lower value of AIC are preferred to models having a larger AIC value. AIC is defined as: $AIC = -2 \times ML + 2 \times k$ Where, ML is the maximum likelihood estimate of the parameters and k is the number of variables in the model.

C. *Model Estimation*

A summary statistics for explanatory variables in the conflict based safety evaluation models are shown in Table III.

In order to investigate the correlation of conflicts with other explanatory variables, conflicts has been modelled against volume of traffic in major and minor roads, volume of NMV and volume of right turning NMVs. The parameter estimates and goodness of fit measures of the models are presented in Table IV.

MODELING CONFLICTS WITH TRAFFIC VOLUME

Model 1 investigates the correlation between simulated conflict and observed hourly traffic volume entering each intersection from the major roads and minor roads. As traffic volume increases in approach roads, drivers find it increasingly difficult to take right turns as well as left turns against the movement of opposing and merging traffic respectively as a result of presence of fewer gaps in traffic stream. Hence, drivers are forced to take more risk prone turning maneuvers, which increases conflicts among vehicles in the traffic stream [19]. From the model, it is evident that both volume of vehicle in major and minor roads are highly significant explanatory variables (p-values for both the covariates are well below 0.05). The coefficients' signs also agree with aforementioned statement, indicating an increase in volume will result in an increase in number of conflicts.

MODELING CONFLICTS WITH NON-MOTORIZED TRAFFIC VOLUME

As volume of NMV increases in traffic stream the overall mobility of entire stream decreases due to lower acceleration capability of NMV. Hence the speed differential among the vehicles decreases which results in lower number of conflicts. The sign of the explanatory variable in this model conforms to this explanation. The covariate is also found to be statistically significant in this model.

MODELING CONFLICTS WITH PROPORTION OF RIGHT TURNING NON-MOTORIZED TRAFFIC VOLUME

It is well known that NMVs are the slowest moving vehicles in a traffic stream, so intersection clearance time during a signal phase is significantly dependent on the time NMVs take to clear the intersection. Right turning vehicles take the longest time to clear the intersection during a signal phase under left hand driving convention. If NMVs constitute a significant portion of vehicles in a traffic stream, there is a higher probability of queue formation in the approach roads of the intersection. In such a scenario, average speed of traffic stream falls resulting in reduced speed differential among vehicles. So a lower number of conflicts should take place when the number of right turning NMVs is higher in an intersection.

A model using observed hourly traffic volume entering each intersection from the major roads and minor roads as covariates and incorporating a dummy variable for proportion right turning NMVs in the intersection (takes value 1 when 10% of total NMVs take right turn, otherwise 0) is developed to investigate this effect. The coefficients have the expected signs which indicate conflicts increases with increase in traffic volume in major and minor roads. The IRR for dummy variable for right turning NMV is 0.68. This indicates that given all other conditions are same, 32% reduction in total conflicts takes place when the percentage of total NMVs in intersection involved in right turn movements exceeds 10%.

VII. CONCLUSION

In this study, the potential of simulated conflicts based safety evaluation model was investigated for non-lane based behaviour of heterogeneous traffic streams at urban intersections of Dhaka. Since presence of large numbers of non-motorized vehicles is a unique characteristic of such traffic streams, it was also felt necessary to explore the role of non-motorized traffic in prevailing safety situation of the intersections.

Six different urban intersections of Dhaka city were selected for this study based on the availability of significant crash count data and compositions of motorized and non-motorized vehicles. It was decided to investigate 8 one hour time periods of the day during which traffic volumes at these intersections were high (during peak hours). VISSIM simulation models were calibrated for the conditions prevailing in the intersections and validated by comparing number of simulated and observed traffic volumes using the GEH statistic. The output trajectory files from the validated simulation model were then analyzed by SSAM to generate the number of simulated conflicts per hour. This was repeated for each hour of the 8 hour time period for every intersection considered in the study.

The simulated conflicts for each hour were then used to model the corresponding number of hourly traffic volumes entering each intersection. The volume and proportion of non-motorized traffic was also used to model conflicts. A dummy variable representing proportion of non-motorized vehicles involved in right turns at the intersection per hour was correlated with simulated hourly conflicts.

It was found that number of hourly simulated conflicts which are better determinants of intersection safety than historical accident counts are highly correlated with traditional explanatory variables in accident prediction models: traffic volumes from major and minor roads entering intersection. The increasing presence of non-motorized vehicles in the traffic stream was seen to contribute to lower number of conflicts. Additionally, proportion of non-motorized traffic involved in right turning maneuvers was found to positively influence the safety situation of the intersections. The results of this study are valid for non-lane based behavior of heterogeneous traffic streams prevalent in urban intersections.

The calibration and validation procedures of the simulation model used in this study were relatively simple in order to make this a viable method of assessing safety at intersections. Detailed multiple step, model calibration and validation procedures should be pursued by researchers for purpose of safety assessment under similar conditions in the future.

SSAM was used in this study to identify critical conflicts using threshold values of TTC and PET. Future studies should use critical conflicts identified at different values of these safety indicators to model accidents in order to find out the simulated conflict based crash prediction model with the best fit for prevailing roadway conditions. In addition, limitations of SSAM with regards to identifying specific type of conflicts in heterogeneous traffic streams should be properly explored in future works.

Attempts should be also made to establish relationships between different conflicts types and different categories of accidents. Finally, the potential of using properties of simulated conflicts to model injury severity of actual crash events need to be explored by researchers in order to arrive at a comprehensive evaluation regarding the potentiality of traffic microscopic simulation for safety assessment purposes.

REFERENCES

[1] Elvik, R., Vaa, T., Erke, A., & Sorensen, M. (Eds.). (2009). The handbook of road safety measures. Emerald Group Publishing.

[2] Chen, P., Zeng, W., & Yu, G. (2019). Assessing right-turning vehicle-pedestrian conflicts at intersections using an integrated microscopic simulation model. Accident Analysis & Prevention, 129, 211-224.

[3] Guo, Y., Essa, M., Sayed, T., Haque, M. M., & Washington, S. (2019). A comparison between simulated and field-measured conflicts for safety assessment of signalized intersections in Australia. Transportation research part C: emerging technologies, 101, 96-110.

[4] Amundsen, F., and Hyden, C. (1977). Proc., 1st Workshop on Traffic Conflicts, Institute of Transport Economics, Oslo, Norway.

[5] Gettman, D., Pu, L., Sayed, T., & Shelby, S. G. (2008). Surrogate safety assessment model and validation: Final report (No. FHWA-HRT-08-051).

[6] Huang, F., Liu, P., Yu, H., & Wang, W. (2013). Identifying if VISSIM simulation model and SSAM provide reasonable estimates for field measured traffic conflicts at signalized intersections. Accident Analysis & Prevention, 50, 1014-1024. doi:10.1016/j.aap.2012.08.018

[7] Cunto, F., & Saccomanno, F. F. (2008). Calibration and validation of simulated vehicle safety performance at signalized intersections. Accident Analysis & Prevention, 40(3), 1171-1179. doi:10.1016/j.aap.2008.01.003

[8] Saleem, T., Persaud, B., Shalaby, A., & Ariza, A. (2014). Can Microscopicsimulation Be Used to Estimate Intersection Safety? Case Studies Using VISSIM and Paramics. Transportation Research Record: Journal of the Transportation Research Board, (2432), 142-148.doi: 10.3141/2432-17

[9] Caliendo, C., & Guida, M. (2012). Microscopicsimulation approach for predicting crashes at unsignalized intersections using traffic conflicts. Journal of Transportation Engineering, 138(12), 1453-1467.doi: 10.1061/(ASCE)TE.1943-5436.0000473

[10] Ozbay, K., Yang, H., Bartin, B., & Mudigonda, S. (2008). Derivation and validation of new simulation-based surrogate safety measure. Transportation Research Record: Journal of the Transportation Research Board, (2083), 105-113.doi: 10.3141/2083-12

[11] Archer, J., & Young, W. (2009). Signal treatments to reduce the likelihood of heavy vehicle crashes at intersections: Microscopicsimulation modeling approach.Journal of Transportation Engineering, 136(7), 632-639.doi: 10.1061/(ASCE)TE.1943-5436.0000125

[12] Nezamuddin, N., Jiang, N., Ma, J., Zhang, T., & Waller, S. T. (2011). Active traffic management strategies: implications for freeway operations and traffic safety. In Transportation Research Board 90th Annual Meeting (No. 11-3091).

[13] Habtemichael, F. G., & de Picado Santos, L. (2012). Safety evaluations of aggressive driving on motorways through microscopic traffic simulation and surrogate measures. In Transportation Research Board 91st Annual Meeting (No. 12-2011).

[14] Mathew, T. V., & Radhakrishnan, P. (2010). Calibration of microscopicsimulation models for nonlane-based heterogeneous traffic at signalized intersections.Journal of Urban Planning and Development, 136(1), 59-66. doi:10.1061/(ASCE)0733-9488(2010)136:1(59)

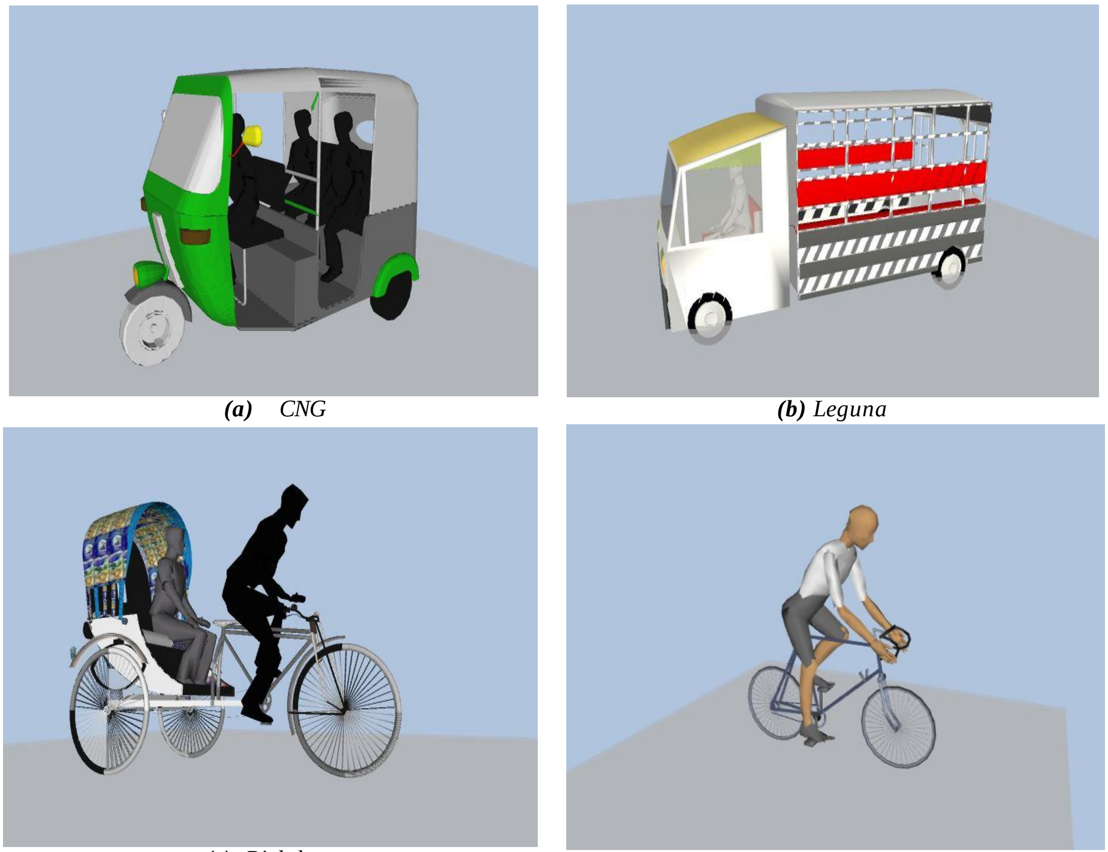
[15] PTV VISSIM 7.0 User Manual, 2014. PTV Planung Transport Verkehr AG, Karlsruhe. Germany.

[16] Sayed, T., Brown, G., & Navin, F. (1994). Simulation of traffic conflicts at unsignalized intersections with TSC-Sim. Accident Analysis & Prevention,26(5), 593-607. doi:10.1016/0001-4575(94)90021-3

[17] Tiwari, G., Mohan, D., & Fazio, J. (1998). Conflict analysis for prediction of fatal crash locations in mixed traffic streams. Accident Analysis & Prevention,30(2), 207-215. doi:10.1016/S0001-4575(97)00082-1

[18] Olmstead, T. (2001). Freeway management systems and motor vehicle crashes: a case study of Phoenix, Arizona. Accident Analysis & Prevention,33(4), 433-447. doi:10.1016/S0001-4575(00)00057-9

[19] Chin, H. C., & Quddus, M. A. (2003). Applying the random effect negative binomial model to examine traffic accident occurrence at signalized intersections. Accident Analysis & Prevention, 35(2), 253-259. doi:10.1016/S0001-4575(02)00003-9



(a) *CNG* *(b) Leguna*

(c) *Rickshaw* *(d)* *Bicycle*

Figure 1 Local Vehicle Models

TABLE I. DISTRIBUTION OF PHYSICAL DIMENSIONS AND KINEMATIC PARAMETERS OF VEHICLES

Vehicle Type	**Length (m)**	**Width (m)**	**Desired Speed (km/h)**	**Acceleration (m/s^2)**		**Deceleration (m/s^2)**	
				Max	**Desired**	**Max**	**Desired**
Rickshaw	2	1.2	15	2.5	2	3	2.5
CNG	2	1.5	40	3.5	2	7.6	2.5
Leguna	3.5	1.5	25	3.5	2.1	6.5	2.5
Bicycle	1.8 – 2	0.5	20	2.5	2	7.5	2.5
Bike	1.45 - 1.8	0.5	45	3.5	3.5	7.5	2.8
Car	4.11 - 4.88	1.8	50	3.5	3.5	7.5	2.8
HGV	6.31 - 10.21	1.5	40	7.3	5.5	5.5	1.3
Bus	11.54	2	30	1.2	1.2	7.5	0.9

TABLE II. CALIBRATED DRIVING BEHAVIOUR PARAMETERS

Parameters		Calibrated Values	Default Values
Car Following			
Look Ahead Distance (m)	*Minimum*	100	0
	Maximum	2000	250
Observed Vehicles		10	4
Look Back Distance (m)	*Minimum*	100	0
	Maximum	1000	150
Average Standstill Distance (m)		0.2	2
Additive Part of Safety Distance		0.28	2
Multiplicative Part of Safety Distance		0.16	3
Lane Changing			
Waiting Time before Diffusion (sec)		39.8	60
Minimum Headway (Front/Rear) (m)		0.1	0.5
Maximum Deceleration for Co-operative Braking (m/s^2)		-5	-3
Overtake Reduced Speed Area		Allowed	Not Allowed
Lateral			
Minimum Lateral Distance (m)	Distance at 0 km/h	0.3	1
	Distance at 50 km/h	0.42	1
Overtake on Same Lane	On Left	Allowed	Not Allowed
	On Right	Allowed	Not Allowed

TABLE III. SUMMARY STATISTICS OF EXPLANATORY VARIABLES IN CRASH PREDICTION MODELS

Explanatory Variable	Mean	Mode	Standard Deviation	Minimum	Maximum
Conflicts	1652.729	443	1630.030306	285	6521
Major Traffic Volume	3126.083	NA	1253.275892	1698	6220
Minor Traffic Volume	2115.417	NA	774.7580771	686	4133
Volume of Non-motorized Vehicles	1118.979	136	791.1987536	136	2484

TABLE IV. PARAMETER ESTIMATES AND GOODNESS OF FIT MEASURES OF CONFLICT PREDICTION MODELS.

	$e^{\beta_0} \times (\mathrm{VHP}_{e,Ma})^{\beta 1} \times (\mathrm{VHP}_{e,Mi})^{\beta_2}$	$e^{\beta_0} \times (\mathrm{VolNMV}_{e,Ma\&Mi})^{\beta_1}$	$e^{\beta_0+\beta_1 Du} \times (\mathrm{VHP}_{e,Ma})^{\beta_2} \times (\mathrm{VHP}_{e,Mi})^{\beta_3}$
Intercept	-13.416 (3.85E-12,1.49E-06)	7.75 (<2E-16,2340.10)	-11.73 (1.69E-10,8.01E-06)
$\mathbf{Log_e}$ of Major Traffic Volume	1.6969 (<2E-16, 5.457)	NA	1.432(4.75E-15, 4.187)
$\mathbf{Log_e}$ of Minor Traffic Volume	0.9239(7.45E-08, 2.519)	NA	1.0069(1.52E-09, 2.737)
$\mathbf{Log_e}$ of Non-motorized Traffic Volume	NA	-3.3E-04 (0.0253,0.99)	NA
Right turning NMVs, greater than 10% of total NMVs (yes 1, otherwise 0)	NA	NA	-0.393(4.67E-03, 0.675)
-2*Log-Likelihood	-737.204	-800.303	-730.229
Over-dispersion	4.9747	1.5377	5.7131
AIC	745.2	806.3	740.23
Scaled Deviance	49.57802	52.98885	49.411
Pearson Value for fit	50.99991	60.2586	52.1822
Pearson Statistic @.10,df	56.3498	57.6785	55.2136

Note: The first value in the parentheses show P-value of each covariate and the second value in the parentheses show Incident Rate Ratios of the covariates

AUTHOR PROFILE

Nayeem Islam

Nayeem Islam received his Bachelors degree in Civil Engineering from Bangladesh University of Engineering and Technology and is currently pursuing his Masters degree from the same university. His areas of interest include microsimulation, supervised learning.

Md. Omar Faruk

Md. Omar Faruk received his Bachelors degree in Civil Engineering from Bangladesh University of Engineering and Technology and completed his Masters degree from University of Central Florida, Orlando, Florida, USA. His areas of interest include automated vehicle, wrong-way driving, arterial management, HSM-based safety analysis, traffic operations, simulation and geometric & structural design of roadways.