

MICRO-SIMULATION OF GAP ACCEPTANCE BY TURNING VEHICLES AT A SIGNALIZED INTERSECTION IN A UNIVERSITY CAMPUS

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Introduction

Turning decision by vehicles, at a signalized intersection in a university campus, is not only dependent on the vehicle's attributes but also on pedestrian and bicycle attributes. Depending on the geometric design, pedestrians may be screened/protected by the presence of cyclists, because in most cases turning vehicles first yield to cyclists then pedestrians. For example, a bicycle path may have an impact on the turning decision of vehicles. The explanatory attributes may also have different extents of impact on the left- and right-turning vehicles. This study considers the intersection of Boulevard de Maisonneuve Ouest and Rue Mackay in George Williams Campus of Concordia University (Montreal, Canada) as a case study. There are two conflict zones at such intersection for the left- and right-turning vehicles. Left-turning vehicles interfere with pedestrians and cyclists at the North-East crossing (Maisonneuve–Mackay), while right-turning vehicles interfere with pedestrians at the West-South crossing (Mackay–Maisonneuve).

This study estimates left- and right-turning vehicles' critical gap acceptance at the selected intersection with a stochastic distribution model. Traffic video data were collected from 10:00 am to 5:00 pm from July to October 2010. A total of 638 traffic data records of left-turning vehicles and 392 records of right-turning vehicles were recorded during the 30-hour period.

Methodology

Vehicles' turning maneuvers at the conflict zone of the signalized intersection are modeled in a two-step process: 1) estimation of the critical gap acceptance (CGA) of the turning vehicles, and 2) determination of the impact of road user's attributes (e.g. pedestrian speed, bicycle speed, vehicles' distance from conflicting zone, pedestrians in group, etc.) and traffic conditions (e.g. traffic jam) on the vehicle's turning decision.

Critical Gap Acceptance (CGA)

The gap acceptance means the amount of time that a vehicle concedes to pedestrian and/or bicycles passing in front of it. A lag is defined as the time needed for a vehicle to reach the conflict zone. A total of 606 of 638 left-turning vehicles accepted the gap, while a very negligible number (32) of left-turning vehicles accept the lag during the left-turning maneuver. Out of 392 right-turning vehicles, only 14 accepted the lag. This study ignores the lag data of left- and right-turning vehicles.

As different vehicles accept different gaps, the estimation of mean value of gap acceptance with randomness for each vehicle is herein suggested. For a critical gap acceptance (CGA), the mean value can be determined as the minimum gap duration accepted by a vehicle in a specific situation (Miller, 1971). The deterministic value of CGA can be identified by measuring the mean of the gap acceptance distribution without considering the randomness and heterogeneity (Taylor and Mahmassani, 1998; Wu et al., 2004). As the gap-acceptance distribution has randomness and heterogeneity, a stochastic mean of gap acceptance per vehicle was determined as the critical gap acceptance.

Several research works (Abernethy, 2004; Alhajyaseen et al., 2011) suggest that gap acceptance probability distributions can be adjusted and fitted by cumulative Weibull distribution. This study fits the probability distribution of gap acceptance by 49 continuous distribution functions. Goodness-of-fit of gap acceptance distributions, compatibility of a random sample with a theoretical probability

distribution function is determined by Kolmogorov-Smirnov (K-S), Anderson Darling (A-D) and Chi-square tests. K-S test quantifies a distance between the empirical and normal (theoretical) CDF. K-S test statistic equals to $\max_{1 \leq i \leq N} \left(F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i) \right)$ (Chakravarti et al., 1967). $F(Y_i)$ is the normal cumulative distribution of gap acceptance distribution being tested. A-D test is a modification of the K-S test and gives more weight to the tails than the K-S test does. The K-S test is distribution free in the sense that the critical values do not depend on the specific distribution being tested. The A-D test is a more sensitive test, which uses the specific distribution in calculating critical values. The A-D test can be defined as $A^2 = -N - S$, where $S = \sum_{i=1}^N \frac{(2i-1)}{N} [\ln F(Y_i) + \ln(1 - F(Y_{N+1-i}))]$ (Chakravarti et al., 1967). Initially, Chi-square goodness-of-fit test is used because it can be applied to any univariate distribution. However, the chi-square test is restricted to discrete distributions. K-S test and A-D test can be applied to determine the goodness-of-fit of continuous distributions. As the distribution of gap acceptance by each vehicle is continuous, the goodness-of-fit of this distribution can better be understood by K-S test and A-D test.

Factors Contributing to Turning Decision Making Process

The simulation of a vehicle's turning maneuvers at the signalized intersection is complicated as it is subjected to complex inter-relationships among pedestrian, vehicle, bicycle and traffic characteristics. Several factors can influence a vehicle's turning maneuvers at signalized intersection such as vehicle speed, vehicle in queue, gap between bicycles/pedestrians allowed vehicles to cross through, pedestrian distance from curb, number of pedestrians in the interference zone, pedestrian speed, and behavior and number of preceding pedestrian(s). Bicycle attributes (cyclists' speed, flow and platooning) may have beneficial circumstances for pedestrians during road crossing decision making process. Turning vehicles, waiting in the queue or at signal tail of green phase, may not give the right-of-way to pedestrians in order to avoid waiting for next green phase of signal cycle.

The contribution of these variables to vehicle's turning decision can be solved by different gap acceptance models. Ben-Akiva and Lerman (1985) and Cassidy et al. (1995) proposed a logit gap acceptance model, while Mahmassani and Sheffi (1981) and Madanat et al. (1994) proposed the use of a probit gap acceptance model. This study applies back-propagation neural network (BPN) for gap acceptance without hypothesizing in advance a certain relationship between dependent and explanatory variables. This study applies BPN based on the mathematical derivation developed by Freeman and Skapura (1991) where the outputs are binary value of critical gap acceptance (1) or rejection (0). In the second step, this study applies binomial logit model (BNL) assuming in advance a certain relationship between critical gap acceptance and explanatory variables.

Back-Propagation Neural Network (BPN). The fundamental concept of BPN networks for a two-phase propagate-adapt cycle is that input variables are applied as a stimulus to the input layer of network units that is propagated through each upper layer until an output is generated. This estimated output is then compared to the desired output, and an error is computed for each output unit. These errors are then transferred backward from the output layer to each unit in the intermediate layer that contributes directly to the output. Each unit in the intermediate layer receives only a portion of the total error signal, based roughly on the relative contribution the unit made to the original output. This process repeats layer-by-layer until each node in the network has received an error that represents its relative contribution to the total error. Based on the error received, connection weights are then updated by each unit to cause the network to converge toward a state that allows all the training patterns to be encoded (Freeman and Skapura, 1991). This research applied generalized delta rule (GDR) to learn the algorithm for the neural network.

Binomial Logit Model (BNL). Probability estimates from the binary logistic regression function can be used to assign the explanatory variables to either of the two categories (accept/reject) of CGA decision model. Statistical significance of prediction ability of BNL CGA decision model for cars and other vehicles (buses, trucks and vans), is tested by assessing different criteria such as sensitivity, log

likelihood statistic, pseudo R^2 (Cox & Snell, and Nagelkerke), and chi-square goodness of fit.

Behavior Analysis of Different Types of Turning Vehicles

Critical Gap Acceptance

Cumulative Distribution Function (CDF) of gap acceptance by right-turning vehicles is best fitted to lognormal distribution function with $\sigma = 0.50246$ (continuous shape) and $\mu = 2.7471$ (continuous scale) parameters (Equation 1). CGA by all vehicles is 17.56 sec with standard deviation 8.46 sec and coefficient of variance (COV) 0.482. K-S test, A-D test and Chi-square test reject the null hypothesis that there is a distance between the empirical and theoretical (normal) CDF.

$$F(x) = \phi\left(\frac{\ln x - \mu}{\sigma}\right), \text{ where } \phi \text{ is the Laplace Integral} \quad (1)$$

The CDF of gap acceptance by different right-turning vehicles (cars and other vehicles) fits to different distribution functions. Like the distribution function for all right-turning vehicles, CDF of gap acceptance by right-turning car is best fitted to lognormal distribution function with $\sigma = 0.51623$ (continuous shape) and $\mu = 2.7593$ (continuous scale) parameters (Equation 1). However, CDF of gap acceptance by other right-turning vehicles is best fitted to log-gamma distribution function $\alpha = 39.36$ (continuous shape), $\beta = 0.06868$ (continuous scale) parameters (Equation 2). The CGA by right-turning car and other vehicles is 17.865 sec and 16.364 sec respectively. CGA was 1.5 sec higher for right-turning cars comparing to that for other right-turning vehicles. Increment of CGA by cars may be resulted from some factors. Although other vehicles start turning maneuver from longer distance to conflict point (turning maneuver was 10.83 m for cars and 17.52 m for other vehicles), higher speed of other vehicles (car speeds 1.96 m/sec and other vehicle speed 2.73 m/sec) reduced the CGA duration comparing to that of cars. At the conflict zone, in 90% cases other vehicles are moving, while in 79% cases cars are moving. These reveal that other vehicles are taking more risk to complete the turning maneuver. Moreover, the pedestrians are also taking less risk to cross the road in front of other

vehicles (pedestrian speeds, interfering car and other vehicles, are 2.03 m/sec and 1.83 m/sec respectively).

$$F(x) = \frac{\Gamma_{\ln(x)/\beta}(\alpha)}{\Gamma(\alpha)} \quad (2)$$

The K-S, A-D, and Chi-square statistics justify the fitness of lognormal and log-gamma cumulative distribution function of gap acceptance by right-turning car and other vehicles respectively.

CDF of gap acceptance, by all left-turning vehicles, best fits to Weibull distribution function with $\alpha = 1.8865$ (continuous shape), $\beta = 16.108$ (continuous scale) and $\gamma = 0.30685$ (continuous location) parameters (Equation 3). CDF of gap acceptance by left-turning car best fits to Burr distribution function with $k = 9.4307$ (continuous shape), $\alpha = 1.9914$ (continuous shape), $\beta = 46.906$ (continuous scale) and $\gamma = 0.22807$ (continuous location) parameters (Equation 4). CDF of gap acceptance by other left-turning vehicles best fits to Rayleigh distribution function with $\sigma = 13.156$ (continuous scale) parameters (Equation 5).

$$F(x) = 1 - \exp\left(-\left(\frac{x-\gamma}{\beta}\right)^\alpha\right) \quad (3)$$

$$F(x) = 1 - \left(1 + \left(\frac{x-\gamma}{\beta}\right)^\alpha\right)^{-k} \quad (4)$$

$$F(x) = 1 - \exp\left(-\frac{1}{2}\left(\frac{x}{\sigma}\right)^2\right) \quad (5)$$

K-S, A-D, and Chi-square statistics justify the fitness of Weibull cumulative distribution function of gap acceptance by all left-turning vehicles. K-S, A-D, and Chi-square statistics of Burr distribution function for gap acceptance by left-turning car rejected the null hypothesis that distribution of data differ from normal distribution. K-S, and A-D statistics of Rayleigh distribution function of gap acceptance by other left-turning vehicles justify the acceptance of null hypothesis, however, Chi-square statistic rejects the null hypothesis that distribution of data differ from normal distribution.

The CGA for all left-turning vehicles is 14.57 sec with standard deviation 7.96 sec and coefficient of variance 0.55. CGA for left-turning car and other vehicles is 14.252 sec and 16.488 sec respectively. CGA is 2.24 sec higher for other left-turning vehicles comparing to that of left-turning cars. This may be resulted from longer distance from conflict point (turning maneuver was 9.44 m for cars and 14.15 m for other vehicles), and higher acceptance of risk by bicycles (bicycle speed was 1.23 m/sec and 1.9 m/sec interfering with cars and other vehicles respectively) and pedestrians (pedestrian speed was 1.97 m/sec and 1.73 m/sec interfering with cars and other vehicles respectively) to pass ahead of the other left-turning vehicles. Other left-turning vehicles are more accommodating to bicycles and pedestrians on the conflict zone comparing to cars as other vehicles provide the right-of-way to more distanced bicycles (1.90 m for cars and 3.84 m for other vehicles) to pass ahead of them.

The comparative statistics of CGA by different types of left- and right-turning vehicles reveal that CGAs of right-turning vehicles are higher than those of left-turning vehicles (20.52% for all vehicles and 25.35% for cars). However, CGA of other vehicles remains almost same in case of both left- and right-turning maneuver.

Factors Contributing to Turning Decision Making Process

Back-Propagation Neural Networks (BPN). A total of 392 gap acceptance data were collected for right-turning vehicles, of which 50% (68% for cars and 59.7% for other vehicles), 31.4% (20.3% for cars and 20.9% for other vehicles) and 18.6% (11.7% for cars and 19.4% for other vehicles) gap acceptance data are assigned to training, testing and holdout respectively. Training data are used to train the neural network, while testing data are used to identify errors during training in order to prevent overtraining. The holdout data are used to assess the final neural network; the error for the holdout data gives a true estimate of the predictive ability of the model because the holdout data are not used to build the model (IBM, 2010). A total of 64.1%, 26.3% and 9.6% of 605 road users' interference data of the left-turning vehicles are assigned to training, testing and holdout. Vehicle's CGA model will not predict the accurate estimation without predicting CGA decision model for all categories of vehicles. This

research calculates the CGA decision model for cars and other vehicles (buses, vans and trucks) by BPN. Multilayer Perception (MLP) network is applied to model vehicle's turning decision in order to minimize the error in predicting default.

BPN model estimates the importance of the selected attributes to the CGA decision by left- and right-turning vehicles. CGA decision model for all right-turning vehicles are mainly determined by vehicle speed (20.09%), number of vehicles passed (16.13%), vehicle moving at the conflict zone (12.98%), and vehicle distance from conflict point (11.02%). It reveals that CGA decision by right-turning vehicles is mainly dominated by vehicle attributes, although pedestrian's speed (1.99 m/sec) is almost equal to vehicle speed (2.09 m/sec), and in 56% and 46% cases pedestrians are crossing the intersection as a group and at rush respectively. Right-turning vehicles are taking risk because in 54% of cases vehicles are in queue, for 37% vehicles are at signal tail, and negligible existence and number of bicyclists at the conflict zone. CGA decisions by left-turning vehicles are determined by pedestrian speed (14.8%), bicycle distance from the conflict point (13.9%), number of vehicle passed (11%), number of bicycles passed during the interference (9.8%), and bicycle speed (8.5%). Therefore, CGA decision by left-turning vehicles is mainly structured by bicycle attributes. However, contribution of input variables to CGA decision model prediction is different for different types of vehicles.

In the case of CGA decision by right-turning cars, vehicle speed (21.42%), vehicle moving at the conflict zone (14.68%), vehicle distance from conflict point (10.12%) number of vehicles passed (8.33%), and pedestrian speed (7.83%) are the determining attributes. Similar to right-turning decision making process by all vehicles, CGA decision model for car is predominately structured by vehicle attributes with exception of pedestrian speed. On the other hand, CGA decision models for left-turning cars are explained by pedestrian speed (9%), existence of bicycle at conflict zone during left-turning maneuver of car (7.5%), bicycles as group (11%), number of vehicles passed (11.5%), and bicycle speed (11.2%).

Significant inconsistency is observed in the importance of input variables for CGA decision model for other vehicles. For example, number of vehicles passed (25.78%), vehicle in queue (17.64%), existence of traffic jam (14.33%), vehicle speed (11.96%), and vehicle turning from turning lane (8.87%) are the dominant contributors of CGA decision model for other right-turning vehicles; while bicycle distance from conflict point (21.5%), bicyclists as group (10.3%), number of vehicles passed (15%), vehicle moving at conflict zone (8.8%), and vehicle turning from turning lane (7.3%) are the most important attributes of decision model for the other left-turning vehicles.

The estimation of BPN CGA decision model has significant difference between values implied by estimators and the true values of the outputs being estimated especially for training data. Testing data, used to track errors during training in order to prevent overtraining, also contain noteworthy expected value of squared error loss. Error for holdout data explains less accurate predictive ability of the constructed BPN MLP network. Moreover, relative error of CGA, a ratio of the sum-of-squares error for CGA to the sum-of-squares error for 'null model' (in which mean value is used as the predicted value), explains significant amount of errors in modeling CGA decision. However, the average overall relative error of model and relative error of dependent variables are fairly constant across the training, testing, holdout data, which give some confidence that the model is not over-trained and that the error in future cases scored by the neural network would be closed to the error. Uncertainty of BPN CGA decision model and irregular attitude of some attributes in defining the CGA decision model persuade this study to validate the CGA decision model for vehicles by applying binomial logit model (BNL).

Binomial Logit Model (BNL). The sensitivity of BNL CGA model depends on how well the model predicts the correct categories of CGA decision-making. BNL CGA models accurately classify 80% (75% gap acceptance and 85.6% gap rejection) and 62% (71.7% gap acceptance and 50.8% gap rejection) cases of CGA by cars; and 100% (100% gap acceptance and 100% gap rejection) and 86%

(87.8% gap acceptance and 84.4% gap rejection) cases of CGA by other vehicles for left- and right-turning maneuver, respectively.

Log likelihood statistic, similar to residual sum of squares in multiple regression, is estimated for determining whether convergence to stable estimates have been attained for CGA decision model for both cars and other vehicles. A small value of log likelihood, for example, 287.141 (at 20th iteration) and 659.371 (at 4th iteration) for CGA model of cars; 39.936 (at 20th iteration) and 60.991 (9th iteration) for CGA model of other vehicles justifies the fitness of BNL CGA models for both right- and left-turning maneuvers, respectively.

Cox & Snell, and Nagelkerke pseudo R^2 , indicators of the amount of variation in the gap acceptance decision explained by the model (from a minimum value of 0 to a maximum value of approximately 1), are estimated to evaluate the goodness-of-fit of logistic models and proportion of CGA decisions explained by BNL CGA models. Cox & Snell pseudo R^2 compares the log likelihood for the logistic model with the log likelihood for the baseline model (without explanatory variables). However, Cox & Snell pseudo R^2 has a maximum value that is not 1. For example, if the prediction of logistic model is perfect, Cox & Snell pseudo R^2 will be less than 1. Nagelkerke pseudo R^2 , analogues to the coefficient of determination R in multiple regressions, is also estimated extending the range of possible pseudo R^2 values to 1. Cox & Snell and Nagelkerke pseudo R^2 values of BNL CGA models of other vehicles suggest that between 74% and 100% of the variability of CGA decision are explained by the explanatory variables for the right-turning vehicles, while between 49.1% and 65.5% variance of CGA decision are explained by the explanatory variables for the left-turning vehicles. BNL CGA models of car suggest that between 39.3% and 52.5% of the variability of CGA decision are explained by the explanatory variables for the right-turning vehicles, while between 10.3% and 13.8% variance of CGA decision are explained by the explanatory variables for the left-turning vehicle. However, BNL CGA models of left-turning cars cannot satisfactorily explain the variance of CGA decisions.

BNL CGA model of right-turning cars identifies vehicle distance from conflict point, vehicle speed, pedestrian in group, pedestrian at rush, vehicle moving at the conflict zone, number of vehicles passed and existence of traffic jam as the significant contributors to the prediction ability of the CGA decision based on the 5% significance level. A unit increase of vehicle speed, pedestrian in rush, and vehicle moving at the conflict zone would result in a decrease of 0.879, 1.326, and 0.97 unit, respectively, in the logit probability of gap acceptance by right-turning car. The logit probability of gap acceptance by right-turning cars will be multiplied by 0.074, 1.107, 1.472, and 0.982 for a unit increase of vehicle's distance from conflict point, pedestrian in group, number of vehicle passed and existence of traffic jam respectively. For the left-turning cars, vehicle in queue, bicycle existence at the conflict zone, bicycle distance from conflict point, bicycle speed, group pedestrians, rush pedestrians, and number of vehicles passed are the significant contributors (5% significance level) to the prediction ability to CGA decision model. A unit increase of bicycle existence at conflict zone, bicycle distance from conflict point, pedestrians at rush, and number of vehicles passed multiplies the likelihood of CGA decision by 7.23, 1.14, 2.19, and 1.64 respectively. On the other hand, unit increase of vehicle in queue, bicycle speed, and group pedestrian decreases the likelihood of CGA decision by 0.41, 0.55, and 0.54 respectively.

BNL CGA model of other right-turning vehicles identifies vehicle in queue, vehicle speed, rush pedestrian, existence of traffic jam, vehicle at signal tail, and vehicles turning from turning lane as the significant contributors to the prediction ability of CGA decision model. On the other hand, vehicle distance from conflict point, vehicle in queue, existence of bicycle at conflict zone, group bicyclists, and bicycle distance from conflict point are the significant contributors to the prediction ability of CGA decision model for the other left-turning vehicles.

This study also estimates Wald test, which is distributed approximately as chi-square on one degree of freedom, to determine the contribution or importance of each attribute. Vehicle speed (22.88%), Number of vehicles passed (19.97%), vehicle distance from conflict

point (9.55%), pedestrian at rush (8.92%), pedestrian in group (7.47%) and vehicle moving at the conflict zone (6.67%) are the predominant contributors to CGA decision by right-turning cars. The predominant contributors of CGA decision for left-turning cars are mainly bicycle (existence of bicycle at conflict zone 6.68%, bicycle speed 6.27%, and bicycle distance from conflict point 4.59%) and pedestrian (pedestrians at rush 12.71% and pedestrians in group 5.77%) attributes along with reasonable contribution by vehicle in queue (9.75%) and number of vehicle passed (4.36%). Long time waiting at queue makes the driver impatient to reject the critical gap. Otherwise, we can summarize that bicycle and pedestrian attributes are the determining factors of CGA decision by the left-turning cars. For the other right-turning vehicles, the paramount contributors of CGA decision are vehicle attributes (vehicle speed 7.51%, vehicle in queue 7.09%, vehicle in signal tail 6.19% and vehicle turning from turning lane 6.45%). However, bicycle attributes (bicycle distance from conflict point 8.71%, group bicycle 6.38%, and existence of bicycle at conflict point 4.49%) are the main decision making factors of CGA for other left-turning vehicles along with some influence of vehicle attributes (vehicle distance from conflict point 8.53%, and vehicle in queue 7.56%). Therefore, for all types of vehicles, CGA decision for left-turning vehicles is predominantly determined by the bicycle attributes followed by pedestrian attributes.

Conclusion

Turning vehicles, at a signalized intersection in a university campus, are frequently impeded by pedestrians and bicycles; therefore, vehicles' turning decisions are very crucial to ensure traffic safety. Vehicles' turning decisions are subject to road users' characteristics and traffic conditions at the signalized intersection. The objectives of this study are to estimate CGA of different turning vehicles, and to determine the influence of road users' attributes on vehicles' turning decisions. This study considers the intersection of Boulevard de Maisonneuve Ouest and Rue Mackay in George Williams Campus of Concordia University (Montreal, Canada) as a case study.

Micro-simulation of turning vehicles' decisions is conducted at two stages—estimation of CGA and determination of the contribution of road users' attributes in the turning decision. Stochastic approaches are applied to estimate the CGA by different vehicles. CDF of gap acceptance by right-turning car is best fitted to lognormal distribution function with CGA of 17.865 sec. CDF of gap acceptance by other right-turning vehicles is fitted to log-gamma distribution function with CGA of 16.364 sec. CDF of gap acceptance by left-turning cars and other vehicles is fitted to Burr and Rayleigh distribution function with CGA of 14.252 sec and 16.488 sec respectively. CGAs of right-turning vehicles are higher than those of left-turning vehicles (20.52% for all vehicles and 25.35% for cars).

Backpropagation learning algorithm of Artificial Neural Network (BPN) and Binomial Logit Model (BNL) are applied to identify the influence of explanatory attributes on the vehicle's turning decision. BPN prediction model identifies vehicle speed (21.42%), vehicle moving at the conflict zone (14.68%), vehicle distance from conflict point (10.12%) number of vehicles passed (8.33%), and pedestrian speed (7.83%) as the determining attributes of CGA decision by the right-turning cars. However, pedestrian speed (9%), existence of bicycle at conflict zone (7.5%), bicycle as group (11%), number of vehicles passed (11.5%), and bicycle speed (11.2%) are the main decision-making factors for the left-turning cars. BPN prediction model also identifies number of vehicles passed (25.78%), vehicles in queue (17.64%), existence of traffic jam (14.33%), vehicle speed (11.96%), and vehicle turning from turning lane (8.87%) as the dominant contributors of CGA decision model for other right-turning vehicles; while bicycle distance from conflict point (21.5%), bicycle as group (10.3%), number of vehicles passed (15%), vehicle moving at conflict zone (8.8%), and vehicles turning from turning lane (7.3%) are the most important attributes of decision model for other left-turning vehicles.

BNL CGA model identifies vehicle speed (22.88%), number of vehicles passed (19.97%), vehicle distance from conflict point (9.55%), pedestrian at rush (8.92%), pedestrian in group (7.47%) and vehicle moving at the conflict zone (6.67%) as the predominant

contributors to the CGA decision by right-turning cars; while bicycle (19.31%) and pedestrian (21.33%) attributes are the predominant attributes of BNL CGA decision model for left-turning cars. For the other right-turning vehicles, the paramount contributors of CGA decision are vehicle attributes (vehicle speed 7.51%, vehicle in queue 7.09%, vehicle in signal tail 6.19% and vehicle turning from turning lane 6.45%). However, bicycle attributes (bicycle distance from conflict point 8.71%, group bicycle 6.38%, and existence of bicycle at conflict point 4.49%) are the main decision-making factors of CGA for other left-turning vehicles along with some influence of vehicle attributes (vehicle distance from conflict point 8.53%, and vehicle in queue 7.56%).

Both BPN and BNL CGA prediction model identifies that CGA decisions by left-turning vehicles are predominantly determined by the bicycle attributes for all types of vehicles, while vehicles' attributes are the major contributors of CGA decision by the right-turning vehicles.

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