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Original Research Paper

Analyzing variations in spatial critical gaps at two-way stop controlled intersections using parametric and non-parametric techniques

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HIGHLIGHTS

- The study provides important insights for determining and analyzing spatial critical gaps of drivers at high speed and medium speed uncontrolled intersections.
- Binary logit model and support vector machines are used as a linear classifiers to fit decision boundary (optimal plane) between two classes i.e., accepted and rejected gaps.
- The spatial critical gaps estimated using BLM and SVM corresponding to 85th percentile speed are 46 m and 45 m respectively for medium speed intersections.
- SVMs have very good potential to be an alternative tool for the estimation of driver's critical gap.

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ABSTRACT

At two-way stop controlled (TWSC) intersections drivers on minor stream are generally at risk because of the difficulty in judging safe gap between major stream vehicles. Any misjudgment by the driver while choosing gap may result in a collision with major stream vehicle. This paper provides important insights for determining and analyzing spatial critical gaps of drivers at high speed and medium speed TWSC intersections. The critical gap line (CGL) fitted for the accepted and rejected gaps using parametric (binary logit model-BLM) and non-parametric (support vector machines-SVM) techniques gives critical gap values at 15th, 50th and 85th percentile speeds. The evaluation of spatial critical gap with respect to major road vehicle (conflicting vehicle) speed makes it easier to understand the impact of variation in speed on spatial gaps accepted by the drivers on the minor road. The logit models developed revealed that the probability of accepting gap decreases with increase in the speed of the conflicting vehicle and it increases with increase in the distance of conflicting vehicle. The spatial critical gaps estimated using support vector machines were found in close approximation with those estimated using binary logit model. The study results showed that SVMs have very good potential to be an alternative tool for the estimation of driver's critical gap. The spatial critical gaps corresponding to 15th, 50th and 85th percentile speeds for medium speed intersections were 32 m, 38 m and 46 m respectively and for high speed intersections these values were 64 m, 76 m and 104 m

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respectively. The increase in the magnitude of gap value with respect to the percentile speed clearly states the effect of speed on spatial gaps. The insights from the study can be used to suggest various measures to improve the safety of crossing drivers at uncontrolled intersections.

1. Background

Critical gap is a key parameter in analyzing capacity and level of service of unsignalized intersections. Critical gap as stated in different studies is the minimum gap accepted by drivers to enter the intersection safely (Brilon et al., 1999; Hewitt, 1985; Raff and Hart, 1950). In HCM 2010 (TRB, 2011) the term "critical headway" is used and is defined as the minimum time interval in the major-street traffic stream that allows intersection entry for one minor-street vehicle. The usage of critical gaps has been limited to finding intersection capacity, level of service and safe sight distance at the unsignalized intersections.

Many past studies deal with time based critical gap (Ashalatha and Chandra, 2011; Brilon et al., 1999; Davis and Swenson, 2004; Hamed et al., 1997; Hewitt, 1983, 1985; Pant and Balakrishnan, 1994; Raff and Hart, 1950; Troutbeck, 1992) and only a few studies are found which investigates the spatial critical gap at unsignalized intersection. One of the obvious reasons that temporal gaps are preferred over spatial gaps is that it integrates both space and speed simultaneously. However, the individual effect of both space and time on drivers crossing behavior is not explained by temporal gaps. Patil and Pawar (2014) modeled temporal and spatial critical gaps at uncontrolled intersection and analyzed the effect of different parameters such as time, speed, distance and vehicle type on driver's gap acceptance behavior.

Some previous studies on drivers' gap acceptance are discussed in brief along with their result outcomes and arranged with respect to progression of research methods/theories. Adebisi and Sama (1989) studied the influence of duration of stopped delay on minor road driver's gap acceptance behavior. The mean and variance of critical gap for different drivers were studied and analyzed. It was found that drivers were relaxed and less aggressive to the gaps when they faced minimal delay, but were found to be more aggressive as the delay faced by the drivers increased. Golias and Kanellaidis (1990) proposed analytical methods for the estimation of the critical gap and lag by relating the major stream flow to the headway acceptance distribution. The analytical approach showed the dependency of given parameters on the traffic flow as well as headway acceptance data. Hamed et al. (1997) used a probit model to find the drivers probability of accepting or rejecting a gap at urban T-intersection, which in turn was used to find the drivers critical gap. The analysis results revealed that mean critical gap is influenced by total opposing traffic flow, number of lanes, presence of a median with a left-turn lane, type of maneuver, speed of major road, and time of the day. Gattis and Low (1999) used different methods (Raff's method, acceptance cure method, Greenshields method, logit method, probit method, Siegloch method) to model the drivers critical gap at a typical stop-controlled intersection. The results from different methods varied widely, thus making it more difficult to choose proper critical gap value. Tian et al. (1999) used maximum likelihood method (MLM) to evaluate the driver's critical gap at two-way stop controlled (TWSC) intersection and the background of MLM for measuring driver's critical gap is well documented. Dissanayake et al. (2002) studied the effect of age difference on gap acceptance behavior at TWSC intersections. The statistical analysis revealed that older drivers' gap acceptance capabilities during day and night were significantly different at 95% confidence interval. Cooper and Zheng (2002) studied turning gap acceptance decision making under the distracted and not-distracted conditions using driving simulator. Under not distracted conditions the driver's gap acceptance judgment was found to be influenced by their age, the gap size, the speed of the trailing vehicle, the level of indecision and the condition of the track surface. However, when distracted, the drivers did not consider pavement surface condition into the decision process.

Yan et al. (2007) modeled the effect of major road vehicle speed and driver age and gender on the left turn gap acceptance using driver simulator experiment. The experiment results showed that the older female drivers displayed conservative driving attitude and also the most vulnerable group for relatively complex driving tasks. McGowen and Stanley (2011) proposed an alternative method to find critical gap for the drivers at TWSC intersection as the maximum likelihood method developed by Troutbeck (2014) might give biased results and cannot be used for the data sets that contain only rejected gaps. Wu (2012) established a model for estimating the critical gap and its empirical distribution. The established model does not require any presumptions regarding the distribution function of critical gaps and drivers behavior. Troutbeck (2014) reviewed the ability of the maximum likelihood technique and the probability equilibrium method to predict the mean and standard deviation of the critical gap with a simulation of 100 drivers, repeated 100 times for each flow condition. The maximum likelihood method gave consistent and unbiased estimates of the mean critical gap; whereas the probability equilibrium method had a significant bias that was dependent on the flow in the priority stream. Pawar and Patil (2018) analyzed the response of major road drivers to aggressive maneuvering of the minor road drivers at unsignalized intersections using driving simulator. The

Table 1 – Characteristics of selected intersections.

Parameter	Medium speed intersection	High speed intersection
Location	NH-166	NH-48
No. of sites	3	2
Area	Urban	Rural
Control on minor street	Stop controlled	Stop controlled
Speed on major street (km/h)	40	60
Major leg	Four lane divided	Four lane divided
Minor leg	Two lane undivided	Four lane divided

major road driver behavior was evaluated with reference to three variables: response time before possible conflict (RTPC), average speed while approaching intersection and at the intersection, and deceleration rate. The analysis results showed that the RTPC values against the right turning vehicles were very low indicating high risk against right turning vehicles (considering left side driving practice). Pawar and Patil (2017) analyzed dilemma of minor road vehicles intending to cross the major road at uncontrolled intersections. The study modeled variations in spatial gap acceptance behavior by different drivers and arrived at dilemma zone boundaries. The study also explains the importance of spatial gaps over temporal gaps to model the dilemma zone boundary values at uncontrolled intersections.

To conclude, gap acceptance theory is limited to finding capacity and LOS of unsignalized intersections, only a few studies have used gap acceptance theory for highway safety considerations. Many gap acceptance studies are reported for homogenous traffic conditions where lane discipline and priorities are respected. A majority of the research used time based gap data for modeling driver's gap acceptance behavior. Spatial gap acceptance behavior of drivers and variations in gap acceptance with respect to the speed at uncontrolled intersections are not comprehensively studied.

The main focus of this paper is to investigate the dynamics of driver's spatial gap acceptance behavior at uncontrolled intersections. This study is first of its kind to analyze and model the variation in spatial critical gap with respect to the approaching vehicle speed. The insights from the research can help transportation professionals and safety analysts to design various traffic safety measures thus improving safety and performance of unsignalized intersections.

2. Intersections selected

Three medium speed (posted speed on major road is 40 km/h) and two high speed (posted speed on major road is 60 km/h) uncontrolled intersections were selected for the study. Table 1 describes the characteristics of the medium speed and high intersections selected. The medium speed 4-legged intersections were located on National Highway-166, whereas high speed 3-legged intersections were located on National Highway-48. Fig. 1 illustrates the geometry of selected 4-legged intersections. The major road is four-lane divided with orientation in east–west direction and the minor road is two-lane undivided. Proper lane markings were present on the roads approaching intersection and the intersection area. Stop signs were present on the minor road. Footpaths were present on both the sides of carriageway and zebra crossings at intersection area. The posted speed on major road was 40 km/h. The drivers were crossing the intersection in two stages: cross the first conflicting movement (W-E movement in Fig. 1), if necessary stop at the median refuge area, then cross the second conflicting movement. Three cameras at different locations were placed to collect all necessary details.

The geometric details of selected 3-legged intersections are shown in Fig. 2. The major and minor roads are four-lane divided with major road oriented in north-south direction. The intersections selected are located on a high speed corridor i.e., national highway-48, the posted speed limit on major road approaching intersection was 60 km/h. The drivers were crossing the intersection in two stages: cross the first conflicting movement (N–S movement in Fig. 2), then cross the second conflicting movement.

3. Research data

The data were collected by video recording traffic flow for 120 min at each intersection during day time from 10 AM to 12 AM. Clear sunny days were selected so that the pavement

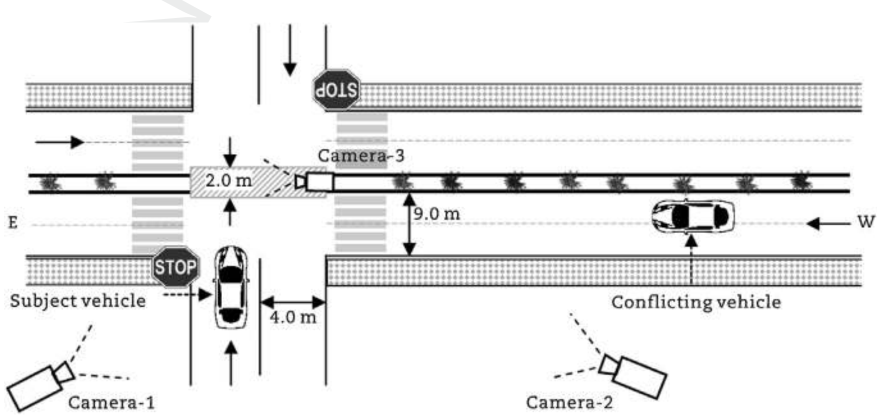

Fig. 1 – Geometry of selected 4-legged intersections.

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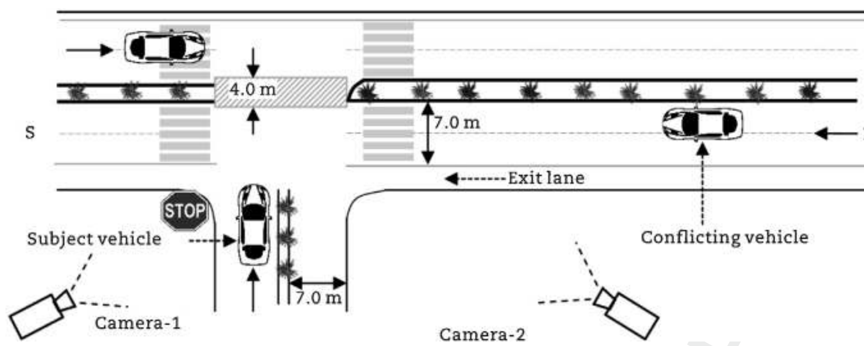

Fig. 2 – Geometry of selected 3-legged intersections.

remained dry during the data collection. Traffic flow on approaches leading towards the intersection and at the intersection area were recorded and analyzed in the laboratory. Speed and the distance of the conflicting vehicle are measured when the subject vehicle is waiting to enter the intersection area. Road markings and traffic cones placed at 5–10 m intervals on the major road were used as reference to measure the distance. The decision of subject vehicle (accepted or rejected) during the course of action is also recorded. Total 1234 gap data at three medium speed intersections and 1735 gap data at high speed intersections were extracted using AVS video editor by playing videos at 30 frames per second. Of all the gap acceptance data extracted, approximately 21% were lags and 79% were gaps for both medium speed and high speed intersections. Spatial lag (first gap) and spatial gap data were merged during the analysis. Fig. 3 depicts a pictorial representation of accepted and rejected gap profiles when subject vehicle is waiting to cross the major road. Red circular profiles represent the rejected gaps by the subject vehicle for a particular distance and speed of the conflicting vehicle. Yellow triangular profiles represent the accepted gaps by the subject vehicle for a particular distance and speed of the conflicting vehicle. In Fig. 3, the accepted and rejected gap profiles are merged with the intersection geometry (not to the scale) for the better understanding of readers.

3.1. *Significance of spatial gaps*

Temporal critical gap are important inputs for estimating capacity and simulating different scenarios of/for uncontrolled intersections. The usage of critical gap has been only limited to finding capacity, LOS and safe sight distance at uncontrolled intersections. Time although accounts for both speed and distance simultaneously, it fails to describe the effect of speed and distance independently. A driver's survey form was designed to understand the driver behavior when he/she approaches the intersection. 160 licensed drivers were surveyed to find out their awareness of, and response to, the uncontrolled intersections. During survey respondents were asked on what basis they judge the gap while crossing at unsignalized junctions. Overall 71% of respondents stated that, distance as one of the important parameter for judging the gap. 60% of respondents combined effect of speed with distance to judge the safe gap. Of all, 21% of respondents judge gap based on distance only, while only 9% respondents judge gap based on time gap (Fig. 4).

While extracting gap acceptance parameters from video data, it was observed that, most of the times for a same value of time gap, some drivers were found to accept the gap and some drivers were found to reject the gap. This behavior of drivers remains unexplained for such a value of time gap. For example, in Fig. 5, Case I represents the situation wherein the subject vehicle is waiting at a stop line and conflicting vehicle is at a distance of 60 m from the conflict point and moving with a speed of 12 m/s (43 km/h), whereas Case II represents the situation with conflicting vehicle at 100 m and moving with a speed of 20 m/s (72 km/h). In both the cases temporal gap available for the subject vehicle is same i.e., 5 s but the available spatial gaps are different i.e., 60 m and 100 m. Therefore, the subject vehicle driver may behave differently

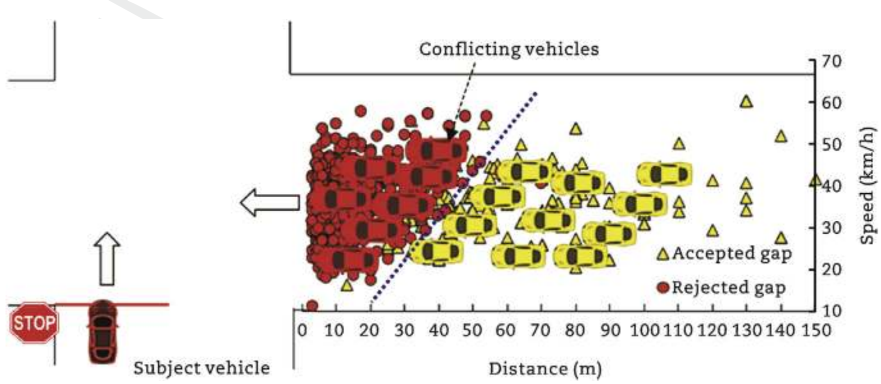

Fig. 3 – Demonstration of accepted and rejected gaps by subject vehicle at intersection area.

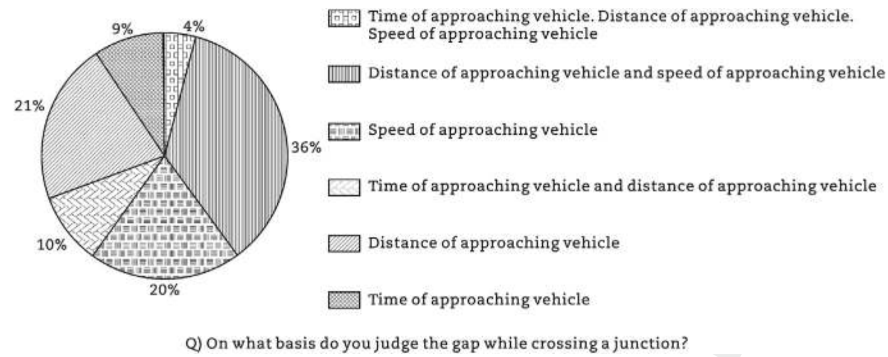

Fig. 4 – Drivers' judgment of gap.

for both the cases i.e., for the first case, driver might reject the gap due to shorter available spatial gap (60 m) and might accept the gap in case-II due to longer available spatial gap (100 m); or the case might be vice versa due to different speeds. The above example is quoted based on the actual observation in the field.

4. Methodology

The accepted and rejected profiles were found to follow certain pattern. For example in Fig. 6, the accepted and rejected profiles vary linearly with speed. The dispersion of accepted and rejected profiles is an interesting observation to analyze and understand the effect of space and time and to find the spatial critical gap at uncontrolled intersections. The spatial critical gap is not a constant value and varies with speed of conflicting vehicle. The varying spatial critical gaps can be obtained by fitting a function to both accepted and rejected profiles such that the data are divided into two categories with some statistical significance. A logistic regression function (parametric approach) and a support vector machine function (non-parametric approach) are used to find varying spatial critical gaps. The spatial critical gaps corresponding to 15th, 50th and 85th percentile speeds are calculated. These values can be used for developing

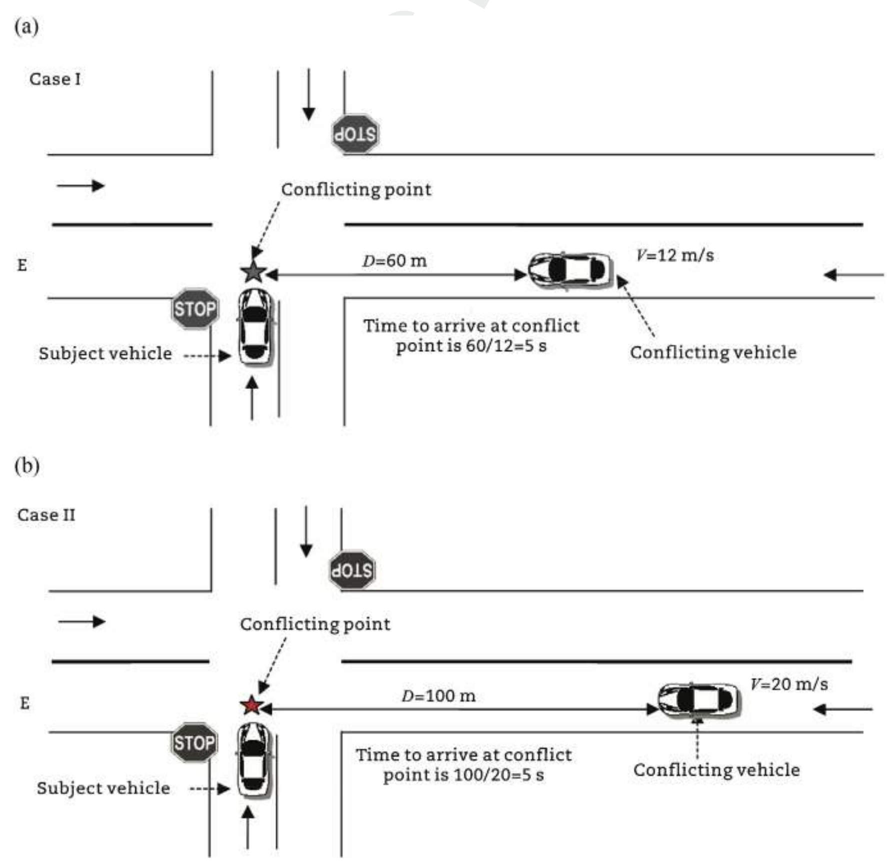

Fig. 5 – Case I and Case II. (a) Case I when conflicting vehicle is at 60 m from conflicting point and moving with a speed of 12 m/s. (b) Case II when conflicting vehicle is at 100 m from conflicting point and moving with a speed of 20 m/s.

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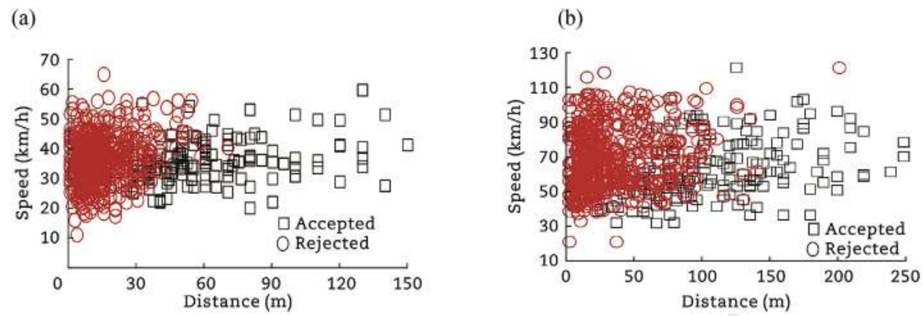

Fig. 6 – Accepted and rejected gaps by subject vehicle at different intersections. (a) Medium speed intersections. (b) High speed intersections.

safety measures at uncontrolled intersections and to analyze the risk taking behavior of drivers.

Fig. 7 depicts 15th, 50th and 85th percentile speed using cumulative frequency distributions at study intersections. The 50th and 85th percentile speeds at medium speed 4-legged intersections are found to be 36 km/h and 44 km/h; whereas, at high speed 3-legged intersections these values are found to be 67 km/h and 87 km/h.

5. Fitting critical gap line (CGL)

5.1. *Parametric approach*

A binary logit model is more often used for studying discrete choices. The general form for the binary logistic model used for modeling driver's gap acceptance behavior is shown in Eq. (1).

$$P_k(i) = \frac{1}{1 + e^{-(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)}} \tag{1}$$

The utility expression, $U_i = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$, gives a desirability of choosing a particular alternative i.e., whether accepted or rejected gap; α is a constant; $X_1, X_2, \cdots, X_n$ are the variables that influence the decision of driver, and $\beta_1, \beta_2, \cdots, \beta_n$ are the corresponding coefficients. An Econometric and Statistics tool NLOGIT was used for developing binary logit models. Logit model was used to obtain critical gaps at different speed values. A line fitting accepted and rejected profiles with probability (P_k) value as 0.5 is termed as CGL. Also, to analyze whether the speed and distance of conflicting vehicle were correlated to the subject vehicles gap acceptance behavior, a model that could predict discrete outcomes was needed.

Table 2 gives the results of estimation of the developed logit model. The *t*-statistic value of all the variables was more than 1.96, indicating their significance at 95% confidence interval.

The variable "speed" has negative coefficient which indicates that higher the speed of approaching vehicle, less is the probability of gap acceptance by the driver on minor road. While the positive and significant coefficient of distance implies that the larger distance the more probability of gap acceptance.

The CGL is obtained using models shown in Table 2. By fixing probability value to 0.5 and finding spatial gaps corresponding to certain values of speed gives CGL. Fig. 8 depicts the CGL using logit model at probability $P = 0.5$ for medium speed intersection and Fig. 9 depicts the CGL for high speed intersection. The slope of CGL clearly indicates that spatial gaps vary with speed. The spatial critical gap values corresponding to 15th, 50th and 85th percentile speeds are depicted in Figs. 8 and 9.

Table 3 gives the critical gap values for medium and high speed intersections at 15th, 50th and 85th percentile speeds. At medium speed intersections the difference in critical gap values is less compared to that of high speed intersections for different values of speed. The value corresponding to 50th percentile speed is termed as mean speed critical gap. The mean speed spatial critical gap can be used to find temporal gap using corresponding speed. The temporal gaps for medium speed and high speed intersections are 3.8 s and

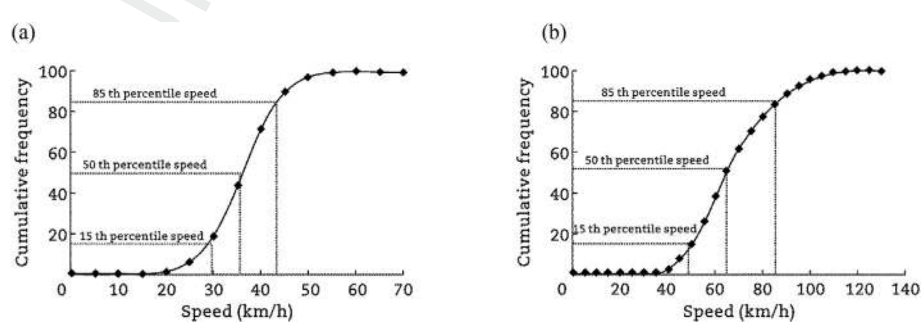

Fig. 7 – Cumulative frequency distributions for approach speeds at study intersections. (a) Medium speed intersections. (b) High speed intersections.

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Table 2 – Results of the estimation of the logit model.

Variable	Coefficient	Standard error	*t*-statistic	*P*-value
Medium speed intersections (McFadden pseudo *R*-squared = 0.65)				
Constant (α)	−1.291	0.647	−1.993	0.046
Speed (km/h)	−0.133	0.020	−6.356	0.000
Distance (m)	0.158	0.011	13.411	0.000
High speed intersections (McFadden pseudo *R*-squared = 0.52)				
Constant (α)	−0.832	0.448	−1.965	0.045
Speed (km/h)	−0.057	0.007	−7.623	0.000
Distance (m)	0.056	0.003	15.807	0.000

4.8 s respectively. The CGL serves both the purposes i.e., in finding spatial critical gap and temporal critical gap. The *x*-intercept of the CGL, when extended, clearly indicates that there are some errors associated with the model developed. This may be due to the nonexistence of data at lower speeds. The projected values of spatial gap at higher speeds will help to understand the effect of high speed on spatial gap acceptance behavior.

5.2. *Non-parametric approach*

SVM is a supervised non-parametric statistical learning technique which discriminates two classes (accepted and rejected) (Fig. 10) by fitting an optimal separating hyperplane (OSH) to the training samples of two classes in a multidimensional feature space (Cortes and Vapnik, 1995). SVM classifiers of the form $f(x) = wx + b$, described by a weight vector w and a bias b learn from the data $D = \{(x_i, y_i)|x_i \in R^d, y_i \in \{-1, +1\}\}_{i=1}^{n}$, where y_i is either 1 or -1, indicating to which the point x_i belongs in a d-dimensional feature space, R^d. $f(x)$ is the discriminant function associated with the hyperplane. The parameter $|b|/||w||$ represents the distance between the optimal separating hyperplane (OSH) and the origin.

The hyperplanes which are parallel to the OSH can be described by the equations $wx - b = +1$ and $wx - b = -1$. The OSH is calculated by maximizing the margin of the two hyperplanes and minimizing the error as shown in Eq. (2).

$$\begin{cases} \min\limits_{w,b,\lambda} \left\{ \dfrac{||w||^2}{2} + C\sum_{i=1}^{n}\lambda_i \right\} \\ w^{\mathrm{T}}x_i + b \geq 1 - \lambda_i \quad i = 1, \cdots, n \\ \lambda_i \geq 1 \end{cases} \tag{2}$$

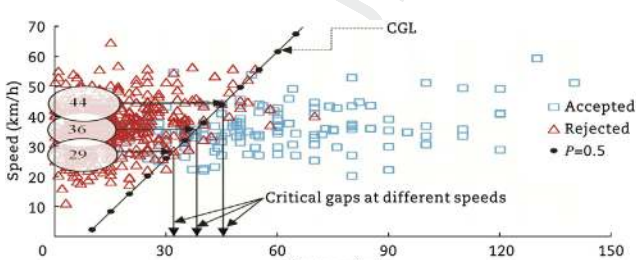

Fig. 8 – Critical gap line using logit model at probability P = 0.5 for gap acceptance data at medium speed intersections.

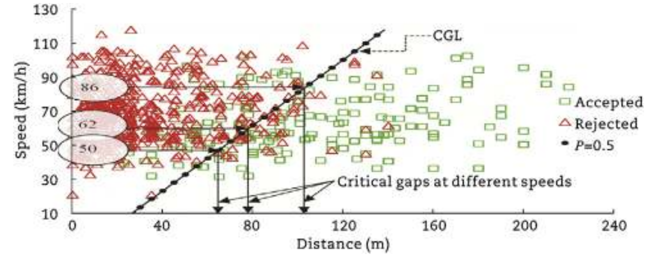

Fig. 9 – Critical gap line using logit model at probability P = 0.5 for gap acceptance at high speed intersections.

The factor C and the slack variable λ_i in Eq. (2) take care of the data points which are non-separable. Factor C applies the penalty for the data points which are located on the wrong side of the hyperplane thus controlling the shape of discriminant function. Minimization problem in Eq. (2) can be solved through Lagrange dual optimization. By introducing Lagrange multipliers α, the constrained problem can be expressed as

$$f(x) = \sum_{i \in m} \alpha_i y_i \Phi(x_i, x_j) + b \tag{3}$$

where m is the set of support vectors, $\Phi(x_i, x_j)$ is a kernel function and α_i are Lagrange multipliers. A detailed description on the general concept of SVM is given by Vapnik (1998), Burges (1998), and Scholkopf and Smola (2001).

Figs. 11 and 12 illustrate a two class linearly non separable classification problem in a two dimensional space. The maximum margin hyperplane gives the maximum separation between the accepted and rejected class. The optimal separating hyperplane represents the CGL. The results of estimation of the developed SVM model were evaluated using Heidke's Skill Score (HSS). The HSS is commonly used in forecasting since it considers all elements from the contingency matrix. Perfect prediction receives HSS = 1, prediction equivalent to the reference prediction receives zero scores, and the predictions worse than the reference prediction receives negative scores. For the data sets corresponding to medium speed intersections and high speed intersections, the HSS values were found to be 0.86 and 0.78 using SVM and 0.78 and 0.77 using binary logit model respectively. The high HSS value indicates that both SVM and binary logit model performs reasonably well. The critical gap values for medium and high intersections at different speeds are reported in Table 4.

6. Results and discussion

The spatial critical gaps corresponding to 15th, 50th and 85th percentile speeds for medium speed and high speed intersections are given in Tables 3 and 4. The spatial critical gaps estimated using parametric approach (binary logit model) and non-parametric approach (support vector machines) corresponding to 85th percentile speed are 46 and 45 m respectively for medium speed intersections. These values are 104 and 105 m respectively for high speed intersections. The spatial critical gap values when divided with corresponding percentile speed give the time gap. The

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Table 3 – Critical gap values for high speed and medium speed intersections at different speeds using BLM.

	Medium speed intersections			High speed intersections		
	15th percentile speed	50th percentile speed	85th percentile speed	15th percentile speed	50th percentile speed	85th percentile speed
Critical gap value (m)	32	38	46	64	76	104

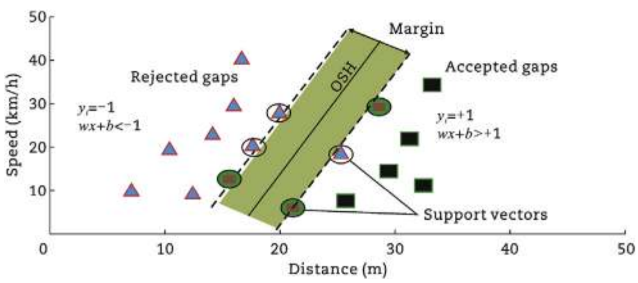

Fig. 10 – Illustration of support vector machine (SVM).

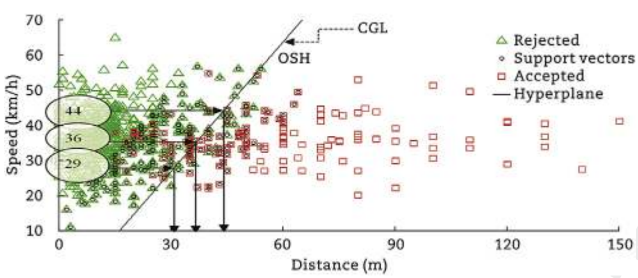

Fig. 11 – Critical gap line using SVM for gap acceptance data at medium speed intersections.

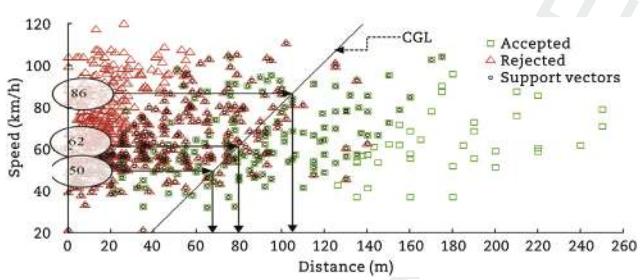

Fig. 12 – Critical gap line using SVM for gap acceptance data at high speed intersections.

mean temporal gaps (corresponding to 50th percentile) for medium speed and high speed intersection are found to vary between 3.6 to 3.8 s and 4.4–4.5 s respectively using BLM and SVM. The spatial critical gap values for high speed intersections are found to be approximately twice of that reported for medium speed intersections. The same was observed using BLM method. The higher value of spatial critical gap at high speed intersection clearly indicates that in general drivers accept longer gaps due to high speed of the conflicting vehicle. Overall, the study results have shown that BLM and SVM perform comparably.

The decision boundary plotted using logistic regression is always linear and therefore logistic regression will work for classification problems were classes are approximately linearly separable. SVM projects the input space to the feature space using a kernel. However binary logit models and SVMs have their own pros and cons. The binary logit model which fits in a group of white box models has presumption on distribution fitting of the data, whereas the black box model such as SVM does not assume any distribution fitting on the processed data. In case of logistic regression the coefficient sizes determine their relative importance for the classification technique, whereas the SVMs do not allow such an interpretation, and can only be verified externally. However, the close estimation between two methods indicates that SVM can be an alternative tool for predicting spatial critical gaps. The variation in spatial critical gaps with respect to speed can be used to suggest various measures to improve the safety of crossing drivers at uncontrolled intersections.

7. Summary and conclusions

Even though the gap acceptance behavior of drivers has been widely explored, very few studies are found that analyse drivers spatial gap acceptance behavior. This research makes an attempt to understand and analyse the effect of speed on driver's spatial gap acceptance behavior at uncontrolled intersections. Two different types of data sets (medium and high speed intersections) were obtained and used to develop BLM and SVM models. The spatial critical gaps obtained at different speeds are compared using proposed methods.

The negative and significant coefficient of speed in BLM indicates that speed of approaching vehicle affects the spatial gap acceptance behavior. The gap acceptance analysis presented in AASHTO (2001) and HCM 2010 (TRB, 2011), which is based on a previous study by Kyte et al. (1996), do not consider the effect of speed of approaching vehicles on the

Table 4 – Critical gap values for medium speed and high speed intersections at different speeds using SVM.

	Medium speed intersections			High speed intersections		
	15th percentile speed	50th percentile speed	85th percentile speed	15th percentile speed	50th percentile speed	85th percentile speed
Critical gap value (m)	32	36	45	68	80	105

gap acceptance decisions. Although the time gap incorporates effect of both speed as well as distance, it fails to explain the effect of magnitude of each individual entity i.e., speed and distance. The coefficients and arithmetic signs of both speed and distance in models developed (Table 1) explains this effect.

Binary logit model and support vector machines are used as a linear classifier to fit decision boundary (optimal plane) between two classes i.e., accepted and rejected gaps. The BLM and SVM are relatively close in their estimation of the spatial critical gap values indicating the usefulness of SVMs in predicting spatial critical gap values. The optimal plane obtained using BLM and SVM is termed as critical gap line (CGL) and is used to find spatial critical gaps corresponding to different percentile speeds. The 15th, 50th and 85th percentile speeds are estimated and corresponding spatial critical gaps are reported for both high speed and medium speed intersections using CGL. The spatial critical gaps corresponding to these percentile values are keys in understanding the gap acceptance behavior of a percentage of driver population and to suggest various measures to improve the safety of crossing drivers at uncontrolled intersections.

The insights from this study can be used to understand the effect of speed on spatial critical gaps, and therefore to estimate the time gap corresponding to speeds observed at study locations. The previous study by Pawar and Patil (2017) demonstrated the use of spatial gaps to estimate dilemma zone and its usage in increasing safety at uncontrolled intersections. Considering the rapid advances in computing technologies, the machine learning techniques are becoming prevalent in various fields, especially to complex problems which involve human decisions. The precise prediction of gap acceptance at uncontrolled road sections using parametric and non-parametric technique is of great importance in developing real time applications such as Advanced Warning and Safety System. Consequently, we believe that employing parametric and non-parametric technique may provide greater behavioral insight with more prediction accuracy. With more data, robust models for estimation of critical gaps can be developed which can be used for developing world traffic. Future studies can collect additional data on traffic, geometric, human factor and weather conditions to analyse and predict the spatial critical gaps for different circumstances.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

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