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Estimation of traffic conflicts using precise lateral position and width of vehicles for safety assessment

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ABSTRACT

Surrogate measures of safety (SMoS) aims at road safety evaluation without depending on historical crash data. Existing studies have evaluated SMoS in traffic conditions having good lane discipline. However, in several traffic conditions vehicles do not follow good lane discipline resulting in high crash rates. Moreover, existing studies do not consider type of the vehicle explicitly while estimating conflicts. This study aims to address these gaps by proposing a generic methodology for safety evaluation applicable also in non-lane-based multi-class traffic conditions. It utilizes precise position of the vehicles and their widths to identify critical interactions between all types of vehicles. Conflicts are then estimated from these critical interactions using the modified time-to-collision (MTTC), an existing SMoS. The proposed methodology is evaluated in both lane-based as well as non-lane based traffic conditions. The former uses NGSIM trajectory data and compares the estimated conflicts with the literature. The latter, on the other hand, uses simulated vehicle trajectories from an expressway but compares the estimated conflicts with historical crash data. The results show that estimated conflicts exhibit significant temporal and spatial correlation with real crashes. It also shows the suitability of the methodology for diverse traffic conditions.

1. Introduction

Traditional road safety evaluation using crash data follows a reactive approach which has many limitations such as small sample size, improper crash records, and missing information about causal factors of the crash (AASHTO, 2010; Tarko et al., 2009). Surrogate measures of safety (SMoS), on the other hand, is a proactive approach that identifies an observable non-crash event that could have led to a crash (Fu et al., 2018; Tarko et al., 2009). This non-crash event thus identified can be further converted into the corresponding crash frequency or crash severity, which can be used for safety evaluation without relying on a huge amount of crash data (Gettman et al., 2008; Tarko et al., 2009).

Most of the existing SMoS are evaluated in traffic conditions characterized by good lane discipline (Kuang et al., 2015; Ozbay et al., 2008; So et al., 2015). However, in several traffic scenarios, vehicles occupy any position across the width of the road. For example, at merging, diverging, and weaving road sections, vehicles do not follow any particular lanes. It is interesting to note that crash rates along such road sections are more than mid-block sections because of frequent lane changes (Lee et al., 2002; Qu et al., 2014; Wang et al., 2015; Yang and Ozbay, 2011). This kind of behavior is also prevalent in mixed traffic conditions (consisting of multi-class vehicles) with non-lane-based movement, where drivers tend to percolate through the traffic along their desired but haphazard path (Asaithambi et al., 2016; Fazio and Tiwari, 1995). Existing SMoS are evaluated mostly in single-class traffic conditions considering the conflicts between passenger cars. These models do not consider the estimation of SMoS between vehicles having different sizes with non-lane-based movement.

This study proposes a methodology to estimate SMoS considering the widths of the vehicles and their precise lateral and longitudinal position on the road. This methodology considers factors such as non-lane-based movement, interactions between different types of vehicles, and all major types of conflicts including rear-end conflicts, side-swipe conflicts, etc. The proposed methodology is generic and can be adapted for different traffic conditions. It is first evaluated using field trajectory data from lane-based traffic condition. It is then evaluated using trajectory data from a microsimulation model of an intercity expressway having multi-class non-lane-based traffic. The study also compares the estimated conflicts with historical crash data.

2. Literature review

The review of the existing SMoS is classified into three categories based on various aspects of surrogate safety estimation. The first

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category considers the existing SMoS with an emphasis on time-based measures. The second category explores the effect of traffic conditions on surrogate estimation. The third category focuses on the application of simulation techniques in the field of safety assessment. Lastly, inferences from this review and the objective of the current study are presented.

2.1. Existing surrogate measures of safety

Numerous SMoS such as time-to-collision (TTC) (Hayward, 1972), post-encroachment time (PET) (Allen et al., 1978), deceleration rate (Gettman and Head, 2003a,b), near-crashes (Guo et al., 2010), and conflicts (Perkins and Harris, 1967) are used in various safety studies. Among these, time-based measures, namely variations of ‘time-to-collision (TTC)’ have been used largely in surrogate analysis, especially on road segments (Behbahani et al., 2015; Yang et al., 2010).

Time-to-collision is defined as the time left for collision provided the speed and course of colliding objects continue to remain the same during a car-following scenario (Hayward, 1972). TTC is a continuous function of time and is calculated for any moment as long as the road users are on a collision course (Hayward, 1972; Laureshyn et al., 2010). Smaller TTC values indicate critical situations (Minderhoud and Bovy, 2001; Ozbay et al., 2008). A minimum TTC value, necessary for safe traffic operations, is termed the *threshold TTC* (Qu et al., 2014). Conflict estimation using TTC relies on motion prediction at a constant velocity and assumes that events such as driver reaction or emergency braking do not take place (St-aubin et al., 2013).

Several studies have attempted to improve the performance of TTC. Time-exposed time-to-collision (TET), is the total duration of exposure to a TTC value less than a threshold value (Minderhoud and Bovy, 2001). Time-integrated time-to-collision (TIT) is the integral of TTC profile (Minderhoud and Bovy, 2001). Rear end collision probability (RECP) combines TTC variation as well as severity (Behbahani et al., 2014). Another variant of TTC is TTC′, which is the rate of change of TTC, and it reflects the changes in driver behavior over time (Behbahani et al., 2015). Comprehensive Time-Based Measure (CTM) quantifies the relative levels of risk associated with each time by combining TTC′, TET, and TIT (Behbahani et al., 2015). One of the main limitations of TTC and its variants discussed above is that it considers only relative speeds and ignores the acceleration of vehicles.

In an attempt to consider acceleration, Ozbay et al. (2008) formulated a relation based on Newton's equations of motion to predict the possibility of occurrence of a conflict. Accordingly, a vehicle interaction at an instant can result in conflict within a certain time if the distance traveled by the following vehicle during that time is greater than or equal to the sum of the initial relative distance between vehicles and distance traveled by the leading vehicle in the same duration of time. This condition is expressed as:

$$v_f t + \frac{1}{2}a_f t^2 \geq d + v_l t + \frac{1}{2}a_l t^2 \tag{1}$$

where, v_f and v_l denote the speed of the following and leading vehicles respectively, a_f and a_l denotes the acceleration of the following and leading vehicles respectively, d is the initial relative distance, and t is the time gap.

The time (t) required to satisfy the conflict criteria mentioned in Eq. (1) is termed as the Modified TTC (MTTC). Denoting Δv and Δa as the relative speed and relative acceleration of the interacting vehicles respectively, MTTC can be derived from Eq. (1) as follows:

$$\text{MTTC} = \frac{-\Delta v \pm \sqrt{\Delta v^2 + 2\Delta \text{ad}}}{\Delta a} \tag{2}$$

Ozbay et al. (2008) computed MTTC from the trajectory data generated using a micro-simulation model (Paramics) of the New Jersey Turnpike and compared with crash data (Ozbay et al., 2008; Yang et al., 2010). The temporal correlation of the estimated conflicts and real crashes indicates that MTTC captures the real-world safety characteristics with a high level of confidence.

2.2. Influence of traffic and temporal conditions on SMoS

SMoS are computed based on intervehicle characteristics obtained from vehicle trajectories. Therefore, SMoS depend on the prevailing traffic conditions. As pointed out by Johnsson et al. (2018), although existing surrogate measures reflect certain aspects of a vehicle interaction, none of the existing surrogate measures seems to capture all aspects. Nevertheless, the choice of a surrogate indicator should be made based on the suitability of that indicator for the traffic scenario considered. Hence, if a surrogate measure developed for a particular traffic situation is to be used in a different scenario, it needs to be evaluated first. However, it can be seen that the existing SMoS are evaluated in single-class traffic conditions involving passenger cars alone (Behbahani et al., 2014; Mahmud et al., 2017). Moreover, existing studies do not consider the interaction between different vehicle types and non-lane-based traffic. The actual width of interacting vehicles seems to play an important role in conflict estimation and is not included in the existing models.

The threshold value of TTC that separate safe and unsafe situations also needs to be determined for varying traffic conditions. Existing studies have adopted different thresholds such as 1 s (Hayward, 1972), 1.5 s (Gettman et al., 2008; Hydén, 1987), 4 s (Hirst and Graham, 1997; Hydén, 1987; Ozbay et al., 2008) and thresholds varying from 2 to 8 s (Behbahani et al., 2015). The threshold value is dependent on the time to respond to a critical situation, which is further dependent on the driver behavior parameters and the road facility itself. Hence, it is difficult to determine a single universal threshold value (Ozbay et al., 2008). Therefore, it is necessary to determine a threshold value suitable for respective traffic conditions (Behbahani et al., 2015).

Although many studies have attempted to evaluate the effectiveness of SMoS in estimating conflicts, they have not focused on estimating conflicts in different environmental conditions such as nighttime. In several traffic conditions, the number of crashes that occur during nighttime is considerably high (Bella et al., 2014; Plainis et al., 2006; Sullivan and Flannagan, 2002; Williams, 1985). Causal factors of nighttime crashes include poor visibility and increased driver distraction due to fatigue or sleep, which require special safety measures (Bella et al., 2014; Chipman and Jin, 2009). An evaluation of MTTC on a study section (Ozbay et al., 2008) showed a good correlation between real crashes and estimated conflicts. However, it may be noted that the nighttime crashes in this study section was very low. Hence, one cannot conclude whether MTTC is effective in estimating nighttime crashes.

2.3. Application of simulation in safety assessment

In the recent past, several simulation-based models have been developed for surrogate safety assessment (Gettman and Head, 2003a,b; Gettman et al., 2008; Sobhani et al., 2013). Simulation technique offers flexibility to evaluate the safety of various design and traffic management options of road facilities before implementing them on the field. This method reduces the labor-intensive process of observing conflicts on the field or extracting trajectories from a large amount of video data (Essa and Sayed, 2015a). Although several simulation models exist, VISSIM (So et al., 2015; Sobhani et al., 2013; Wang and Stamatiadis, 2013, 2014), Paramics (Klunder et al., 2006; Ozbay et al., 2008) and Aimsun (Gettman and Head, 2003a,b) are the most frequently used microsimulation models in safety study. Since simulation is an environment that is programmed assuming safe moving vehicles, it requires calibration and validation for the real traffic conditions to be used for safety analysis. Several studies demonstrate the potential of microsimulation models in safety assessment (Essa and Sayed, 2015a,b; Gettman et al., 2008; Wang and Stamatiadis, 2014). Although these studies establish the adequacy of simulation for safety studies, only a few studies have compared the conflicts estimated with historical crash data (Ozbay et al., 2008; Yang et al., 2010).

2.4. Inferences

Several specific inferences can be drawn from the above review. First, most of the existing surrogate measures deal with crashes involving only passenger cars. Conflicts which occur between different vehicle-types of different static and dynamic characteristics are ignored in most of the studies. Second, the procedure to estimate SMoS assumes that the drivers follow lane discipline, which may not be true for all traffic conditions. Along the merging, diverging, and weaving sections of the road, vehicles occupy positions across the width of the road stretch, irrespective of the lanes. Such a behavior is also common in mixed traffic conditions where vehicles haphazardly percolate through the traffic. Finally, none of the studies have explicitly evaluated the effect of night conditions on conflict estimation, although night crashes are very high on several stretches.

Considering these limitations, this study proposes a generic methodology for estimating SMoS using precise position (both lateral and longitudinal) of the vehicles and their widths. This methodology should work for both lane-based and non-lane-based traffic conditions and should be capable of estimating conflicts between all types of vehicles in both single-class as well as multi-class traffic scenarios. SMoS used in the proposed methodology is the modified time-to-collision (MTTC). Conflicts are estimated for lane-based traffic conditions using NGSIM's trajectory data. Conflicts are also estimated for an access-controlled intercity expressway characterized by multi-class, non-lane-based traffic, using simulated trajectory data. The study also analyzes the sensitivity of the threshold value in estimating conflicts. Further, the estimated conflicts are compared with historical crash data to evaluate both temporal and spatial correlations. The study also evaluates the effect of nighttime conditions on conflict estimation.

3. Methodology

The study aims to develop a generic procedure to estimate a SMoS, considering both lane-based and non-lane-based traffic movement as well as the presence of different types of vehicles. The proposed methodology consists of four broad steps (Fig. 1). First, from every instant of the vehicle trajectory, critical interactions having the potential for collision are identified. Second, MTTC is computed for all the interactions identified.

Third, the threshold value of MTTC is estimated. Finally, MTTC values of all the identified critical vehicle interactions are compared with the MTTC threshold to estimate the number of conflicts. Each step of this methodology is discussed below.

3.1. Identifying critical vehicle interactions

In traffic conditions where there is no good lane discipline, vehicles advance based on the lateral and longitudinal gaps available. Such movements lead to scattered positioning of vehicles across the road stretch at any instant (Bangarraju et al., 2016). In such cases, since there is no well-defined leader, it is meaningless to have a continuous TTC profile. Hence, a suitable procedure is needed to identify critical vehicle interactions.

To identify such critical interactions, intervehicle characteristics such as longitudinal gap and lateral overlap can be used (Kanagaraj et al., 2015). In non-lane-based traffic with weak car-following behavior, there arises a need to identify the interacting vehicles. In such cases, a virtual strip of width equal to the width of the subject vehicle is considered along the road segment (Fig. 2).

It is assumed that any vehicle ahead of the subject vehicle which overlaps the virtual strip of the subject vehicle has a chance of collision. When multiple overlapping vehicles occupy the strip ahead, the one nearest to the subject vehicle is considered for obvious reasons. The concept of lateral overlap, longitudinal gap, and the virtual strip is illustrated in Fig. 2. Longitudinal gap (g_x) between two vehicles is the clear gap in the direction of movement, measured between the front of the subject vehicle and the rear of the interacting vehicle. Lateral overlap (g_y) is the extent to which the width of the interacting vehicle overlaps the width of the subject vehicle. It is the least distance between the opposite edges of the two vehicles (Kanagaraj et al., 2015). The longitudinal gap (g_x) and lateral overlap (g_y) can be computed using the following expressions:

$$g_x = x_i - x_s - L_i \tag{3}$$

$$g_y = |y_i - y_s| - \frac{w_i}{2} - \frac{w_s}{2} \tag{4}$$

where (x_s, y_s) is the front center coordinate of the subject vehicle, (x_i, y_i) is the front center coordinate of the interacting vehicle, w_s is the width of the subject vehicle, w_i is the width of the interacting vehicle, and L_i is the length of the interacting vehicle.

An interaction between two vehicles is identified as critical if the path of the subject vehicle is overlapped by the other vehicle. In other words, these interactions are critical if the longitudinal gap is greater than zero and the lateral overlap is less than zero. Such critical interactions are identified for every vehicle in the traffic stream at every instant. This completes the first step of the methodology.

3.2. Modified time-to-collision (MTTC)

Once a critical interaction is identified, the condition that it will lead to a conflict needs to be determined by computing the MTTC. Ozbay et al. (2008) defines such conditions based on the relative speed (Δv), gap maintained (d), and relative acceleration (Δa). MTTC thus derived is shown in Eq. (2). From this equation, MTTC can have two values, namely t_1 and t_2 as shown below:

$$t_1 = \frac{-\Delta v + \sqrt{\Delta v^2 + 2\Delta \mathrm{ad}}}{\Delta a},\ t_2 = \frac{-\Delta v - \sqrt{\Delta v^2 + 2\Delta \mathrm{ad}}}{\Delta a} \tag{5}$$

Note that the original TTC (t_3) is computed as

$$t_3 = \frac{d}{\Delta v}, \tag{6}$$

and is relevant when the relative acceleration is less than or equal to zero. Depending on the magnitude of Δa, t_1, t_2, t_3, MTTC can have different values as shown below (Ozbay et al., 2008):

$$\mathrm{MTTC} = \begin{cases} \min(t_1, t_2) & \text{if } \Delta a,\ t_1,\ t_2 > 0 \\ t_1 & \text{if } \Delta a,\ t_1 > 0,\ t_2 \le 0 \\ t_2 & \text{if } \Delta a,\ t_2 > 0,\ t_1 \le 0 \\ t_3 & \text{if } t_3 > 0 \text{ and } (t_1, t_2 \le 0 \text{ or } \Delta a \le 0) \\ \text{not defined} & \text{otherwise (relatively safes cenarios)} \end{cases} \tag{7}$$

3.3. Threshold estimation

After estimating MTTC of all the critical interactions identified, a threshold value of MTTC needs to be determined to separate conflicts from the critical interactions. All critical interactions with MTTC below the threshold is considered as potential conflicts. To estimate the threshold value, conflicts were computed for multiple threshold values from 0.5 to 4.0 s, varying at the rate of 0.5 s. The estimated conflicts corresponding to each threshold value are then compared with the crash data, and the threshold value corresponding to the minimum error is adopted.

3.4. Estimating conflicts for a traffic stream

The steps discussed above are used to estimate the possibility of

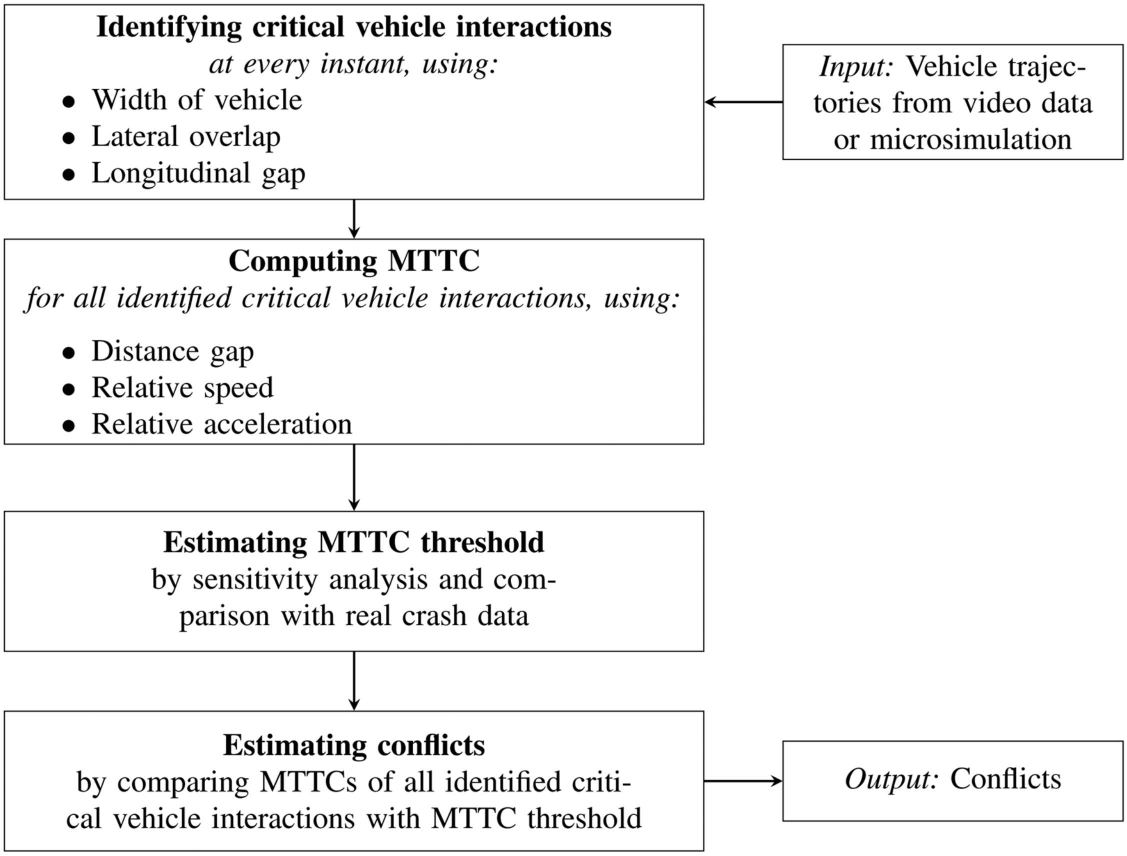

Fig. 1. Flowchart showing the key steps of the methodology for estimating conflicts.

conflict for a pair of interacting vehicles. The same has been extended to estimate conflicts from a traffic stream. The trajectory data can be of any time duration along any length of the road.

4. Evaluation in lane-based traffic

Application of the above methodology for any traffic stream will yield the conflicts of that stream. This methodology needs to be evaluated in both lane-based and non-lane-based traffic conditions. This evaluation can be done by comparing the results from this methodology with the results from the two existing models proposed by Talebpour et al. (2014), and Gettman et al. (2008). Data collection, analysis, and results of this comparison are discussed in the following subsections.

4.1. Data collection

The data for this evaluation is obtained from the Next Generation Simulation (NGSIM) program (Cambridge Systematics, 2005a,b; U.S. Department of Transportation-FHWA, 2006a,b). The data set consists of two road sections, namely a 500 m stretch of the eastbound I-80 in the San Francisco Bay area and a 640 m stretch of the southbound US 101 located in Los Angeles. The trajectory data for these sections for 45 min obtained from field videography is available. Trajectory data for these sections were also obtained from a simulation model of the section created using VISSIM. The model was calibrated using the procedure and driving behavior parameters proposed by an earlier study conducted for the same road section (Menneni et al., 2008).

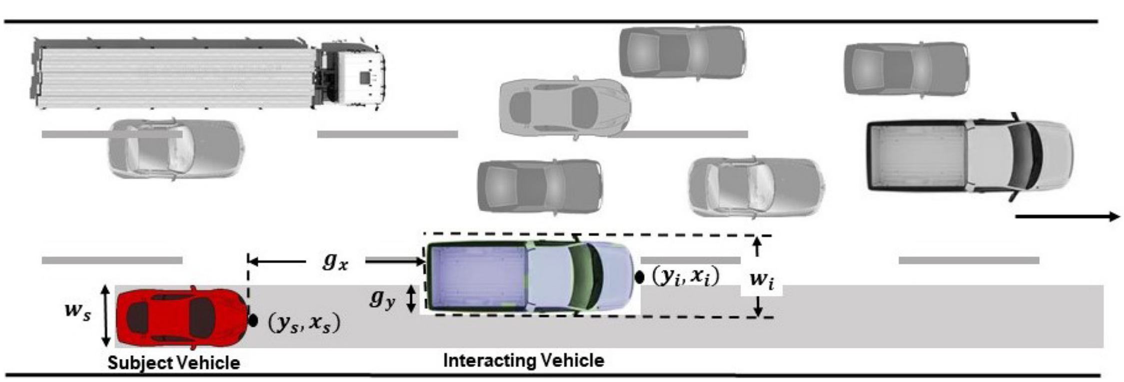

Fig. 2. Illustration of longitudinal gap (g_x), lateral overlap (g_y), and virtual strip for identifying interacting vehicles.

4.2. Analysis and results

Conflicts were estimated based on the proposed methodology using NGSIM trajectory data for different MTTC thresholds varying from 0.5 s to 4.0 s, at an interval of 0.5 s. These conflicts were then compared with the conflicts estimated by the two existing models.

First, these conflicts were compared with the near crashes identified by Talebpour et al. (2014) based on the driver-specific thresholds from NGSIM trajectory datasets. It may be noted that the threshold values by Talebpour et al. (2014) were represented in terms of maximum spacing and hence cannot be directly correlated with the results obtained from the current study. However, a comparison was achieved by considering the spacing, and the average speed to arrive at headways, which correspond to the threshold values used in the present study.

Second, the conflicts from the proposed methodology was also compared with the conflicts estimated using the surrogate safety assessment model (SSAM), which identifies conflicts based on PET and TTC (Gettman et al., 2008). The conflicts were estimated from the simulated trajectories for different TTC thresholds varying from 0.5 s to 4.0 s, at an interval of 0.5 s. The conflicts thus estimated through the proposed methodology, the near crashes identified by Talebpour et al. (2014), and the conflicts estimated through SSAM (Gettman et al., 2008) are tabulated in Table 1.

It can be seen that the number of near crashes identified by Talebpour et al. (2014) on I-80 is more than that on US 101. The same trend can be observed in the conflicts estimated based on the proposed methodology, whereas the conflicts estimated based on SSAM (Gettman et al., 2008) yield an opposite trend. Further, the magnitude of the near crashes identified by Talebpour et al. (2014) is similar to that estimated based on the proposed methodology. Hence, it can be concluded that the results obtained using the proposed methodology are comparable with the existing methodologies for conflict estimation in lane-based traffic conditions. The number of conflicts estimated based on SSAM (Gettman et al., 2008) is much higher than the other two methods. Conflict estimation based on proposed methodology using MTTC is expected to predict more conflicts than conventional TTC since the width of the vehicles are considered. However, an opposite trend is observed here. One possible reason is that the MTTC conflicts were computed using NGSIM trajectory data based on the proposed methodology, whereas TTC conflicts were calculated from simulated trajectory data based on SSAM. This weak correlation could also be attributed to the limitations in SSAM to estimate the conflicts along road segments.

Two limitations can be observed from this comparison: First, the near crashes identified by Talebpour et al. (2014) and SSAM (Gettman et al., 2008) were not compared with real crash data. Second, these two existing models used in the comparison were studied under lane-based traffic conditions. Hence, the proposed methodology needs to be evaluated using crash data from non-lane based traffic.

Table 1
Comparison of conflicts estimated on I-80 and US 101.

Conflicts based on proposed methodology								
Threshold MTTC (s)	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
I-80	0	1	6	13	21	29	38	44
US 101	0	1	2	5	9	16	23	29
Near crashes identified by Talebpour et al. (2014)								
Maximum spacing (m)	3	9	12	18	21	27	30	36
I-80	0	12	24	69	84	106	117	123
US 101	0	0	1	4	4	5	7	7
Conflicts estimated based on SSAM (Gettman et al., 2008)								
Threshold TTC (s)	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
I-80	15	42	112	268	455	664	928	1458
US 101	52	150	317	710	1167	1701	2406	3995

5. Evaluation in non-lane-based traffic using crash data

Having established the effectiveness of the proposed methodology for lane-based traffic, the same needs to be established for non-lane-based traffic, and results have to be compared with crash data. Hence, conflicts were estimated on a 94.5 km long expressway (a six-lane, concrete, high-speed, and access-controlled tolled expressway connecting Mumbai and Pune, two major cities of India). Data collection, analysis, and results for this comparison are discussed in the following subsections.

5.1. Crash data along the study section

The crash data for 3.5 years, starting from October 2012 to March 2016, which included the type of crash, location, date and time of occurrence, number of vehicles involved, and severity, was obtained (JP Research, 2014). A preliminary crash analysis of the study stretch revealed a variety of crash types that occurred along the road. To compare the temporal variation of different types of crashes, the number of crashes in each crash type was normalized and plotted against the time of day, as shown in Fig. 3. It can be seen that all types of crashes follow a similar pattern throughout the day. Hence, it can be inferred that the proportion of different types of crashes is independent of the time of the day. However, past studies show that crashes during daytime and nighttime are caused by different factors (Chipman and Jin, 2009).

To verify this, the actual cause of crashes during daytime is compared to that of nighttime. Time of the day was segregated into daytime (06:00 h to 22:00 h) and nighttime (22:00 h to 06:00 h) (Bella et al., 2014). The accident information sheet containing details of each crash was used to arrive at the percentage of causal factors. The percentage of crashes during daytime and nighttime is plotted against various causal factors and is shown in Fig. 4.

This result indicates that the major causal factors of daytime crashes are sudden unexpected events, driver inattentiveness, vehicle defects, speeding, and other unknown reasons. On the other hand, the major cause of crash during nighttime is driver-inattentiveness. Thus, it can be seen that even though the proportion of different types of crashes are more or less same during daytime and nighttime (Fig. 3), the actual cause of the crash is different during daytime and nighttime (Fig. 4). Hence, it becomes important to ensure that these factors get reflected while estimating the conflicts.

5.2. Geometric and traffic characteristics along the study section

The first 40 km of the expressway, which is a representative section of the entire expressway, is selected as the study section (Fig. 5).

The geometric characteristics such as the radius of turn and gradient were collected using a VBox instrument by traversing multiple times along the study section (Charly and Mathew, 2019). It was observed that the first 35 km of the study section is nearly straight with slight up and down gradients. The last 5 km is characterized by a sharp radius of curvature and steep gradients occurring due to terrain conditions. These factors influence crashes and needs to be considered in safety analysis.

Classified 24-h traffic volume was collected from the stretch. It comprised of 83% passenger cars, 3% buses, and 14% commercial vehicles including both light and heavy ones. It may be noted that two-wheeled motorbikes and three-wheeled auto-rickshaws are not permitted in this study section. However, the traffic still consists of fast-moving vehicles like cars and pickups and slow-moving heavy vehicles like buses and trucks with varying width, acceleration, and speed. Even though lane marking is available on this study section, vehicles often occupy any position across the width of the road based on space availability, leading to non-lane-based traffic.

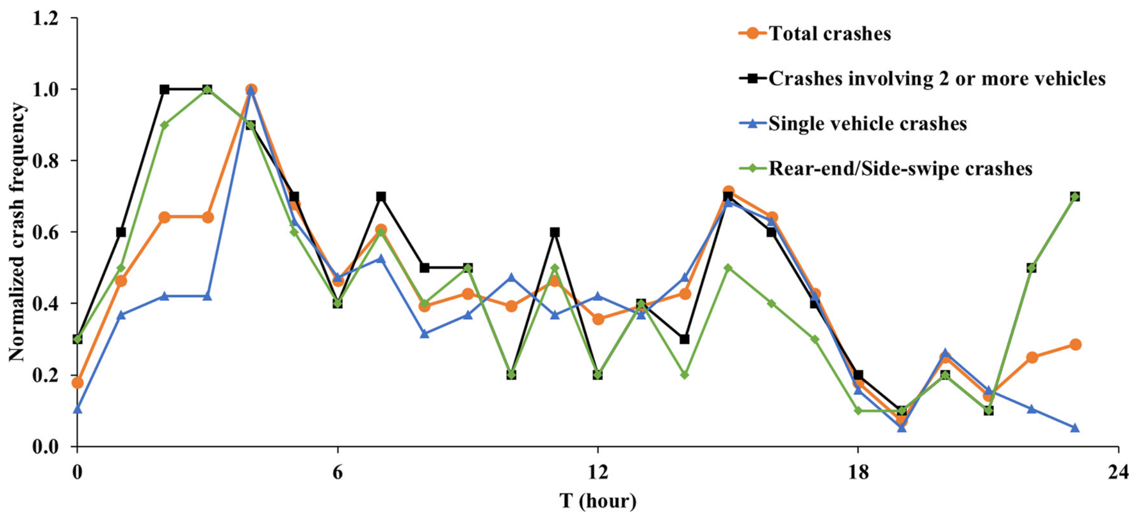

Fig. 3. Proportion of different types of crashes on the study stretch.

5.3. Data required for MTTC estimation

Width of the vehicles and their positions were required for the implementation and evaluation of the proposed methodology. Also, a comparison between daytime and nighttime conflicts required data for a considerable duration. Hence, the vehicle trajectories were generated using VISSIM; an accurate microsimulation model frequently used also in safety studies (So et al., 2015).

The geometric characteristics collected were used to create the microsimulation model of the study section. The model was calibrated using the procedure and driving behavior parameters suggested by Siddharth and Ramadurai (2013) for similar traffic conditions. The actual hourly traffic volume was given as input to the microsimulation model along with vehicle composition and speed distributions. Initial warm-up time was provided, taking into consideration the length of the road stretch and diverse vehicle characteristics. The traffic was simulated for 24 h in addition to the initial warm-up period. The trajectory data were extracted for all vehicles for this 24 h. Hourly traffic volume and speed data were also extracted. The traffic was simulated multiple times using different random seeds to eliminate any bias.

5.4. Analysis and results

The trajectory data thus obtained was processed for every second to estimate conflicts. MTTC threshold was computed by comparing conflicts corresponding to varying thresholds with crash data. The conflicts corresponding to this threshold is used further in the analysis. Conflicts thus estimated and the real crashes were compared with the time of the day, the traffic volume, and the crash location.

5.4.1. Relation between MTTC threshold, estimated conflicts, and real crashes

To arrive at an accurate MTTC threshold, conflicts were estimated assuming threshold values varying from 0.5 s to 4 s at an interval of

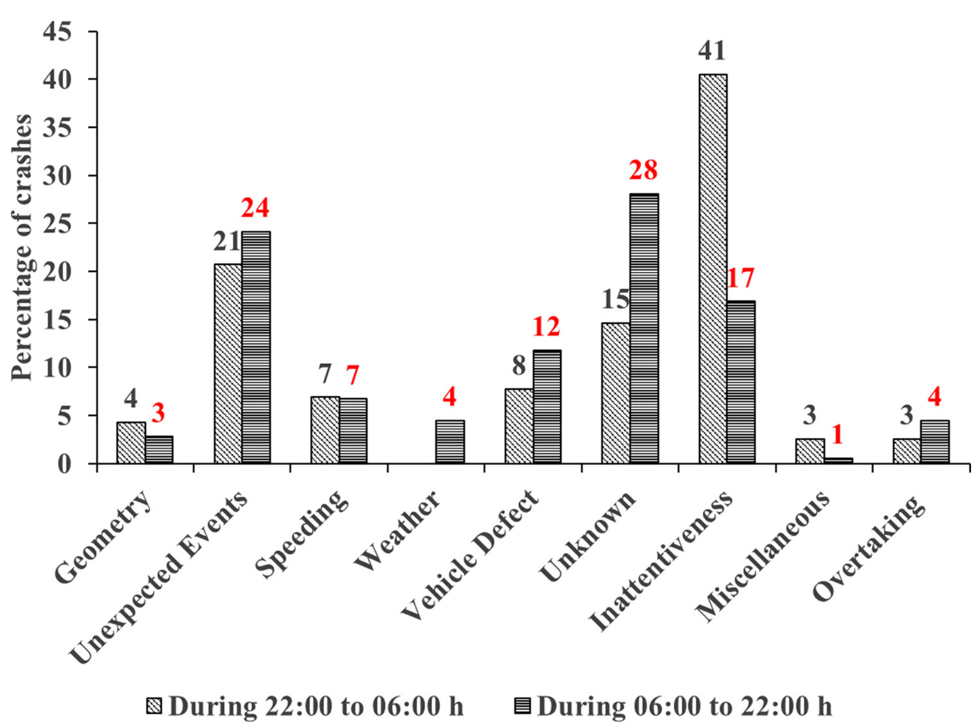

Fig. 4. Crash influencing factors on the study stretch.

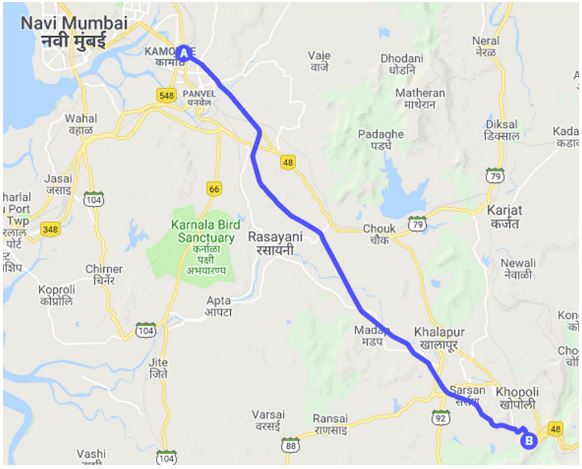

Fig. 5. Study stretch on the expressway

0.5 s. The range of threshold was chosen based on previous studies (Behbahani et al., 2015; Hydén, 1987; Ozbay et al., 2008). The frequencies of the conflicts corresponding to each threshold value were normalized by dividing the individual hourly conflicts with the maximum number of conflicts corresponding to that threshold. To assess the accuracy and reliability of the simulated results, normalized hourly estimated conflict frequencies for different thresholds were compared with the normalized hourly real crash frequencies, and the results are illustrated in Fig. 6. It can be observed that the maximum crashes occurred at 04:00 h, whereas the maximum conflicts were estimated at 15:00 h. Since the period from 22:00 h to 06:00 h correspond to negligible estimated conflicts, this was separated and the remaining period from 06:00 h to 22:00 h was normalized and plotted separately, as shown in Fig. 7. The analysis period from 06:00 h to 22:00 h is referred to as daytime and that from 22:00 h to 06:00 h is referred to as the nighttime based on previous studies (Bella et al., 2014). It can be observed that the maximum estimated conflicts and the maximum real crashes occurred during 15:00 h. Thus, it can be inferred that during daytime, normalized hourly estimated conflict and crash frequencies for different thresholds follow a similar trend. However, the accuracy of estimation of conflicts varies with the threshold values.

To estimate the optimal threshold, the correlation between real crashes and the conflicts estimated based on different thresholds was estimated using two measures. First is Pearson's product moment correlation, which measures the strength of the linear relationship between the variables and whose values may vary between −1 and +1 (Cafiso and Cava, 2009; Witte and Witte, 2009). Second is Spearman's rank correlation coefficient, which is a measure of association between rankings of two variables that is often used as a nonparametric alternative to the traditional coefficient of correlation (Cafiso and Cava, 2009). Both these coefficients were computed for real crashes and estimated conflicts (for different thresholds), as shown in Table 2.

Pearson's correlation coefficients show that there is a statistically significant relationship between the real crashes and estimated conflicts for all thresholds at 99% level of confidence (p-value less than 0.01). Spearman's rank test shows that the conflicts estimated at a threshold of 1 s are correlated with the real crashes at 99% level of confidence. As the conflicts estimated corresponding to an MTTC threshold of 1 s have the best rank correlation with real crashes, 1 s is adopted as the MTTC threshold value. It may be noted that a threshold value of 1 s is very low compared to the threshold values used largely in single-class traffic conditions having good lane discipline (Behbahani et al., 2014; Ozbay et al., 2008). This indicates the distinctive driver behavior observed in non-lane-based and multi-class traffic and justifies the need of a separate methodology to identify conflicts.

5.4.2. Temporal distribution of estimated conflicts and real crashes

MTTC needs to be validated with historical crash data or observed conflict data, in order to use it as a measure of safety (Yang et al., 2010). For this purpose, normalized hourly estimated conflicts were compared with the normalized hourly real crashes, as illustrated in Fig. 8. It can be observed that the estimated conflict frequency pattern matches the real crash frequencies during daytime. Hence, it can be concluded that the parameters used in MTTC computation such as relative speed, relative acceleration, and varying lateral gap and longitudinal gap between vehicles are able to explain the daytime crashes.

On the other hand, during nighttime, real crash frequencies are much high with the highest value observed at 04:00 h. Nevertheless, MTTC could not identify any conflicts during this period. A possible explanation may be that during this time, drivers tend to doze off or get distracted because of poor visibility and fatigue. Such driver characteristics are not considered in the computation of MTTC. Also, higher speeds maintained at night due to low traffic volume might be causing more crashes. It may be noted that MTTC estimation uses relative speed and acceleration, but does not consider their absolute values. Hence, the effect of higher speed is not considered. During nighttime, because of low traffic volume, the lateral and longitudinal gaps between vehicles are large. Hence, identifying conflicts based on intervehicular characteristics, such as MTTC, might fail because of the larger headway between vehicles. However, even in these cases, crashes occur at

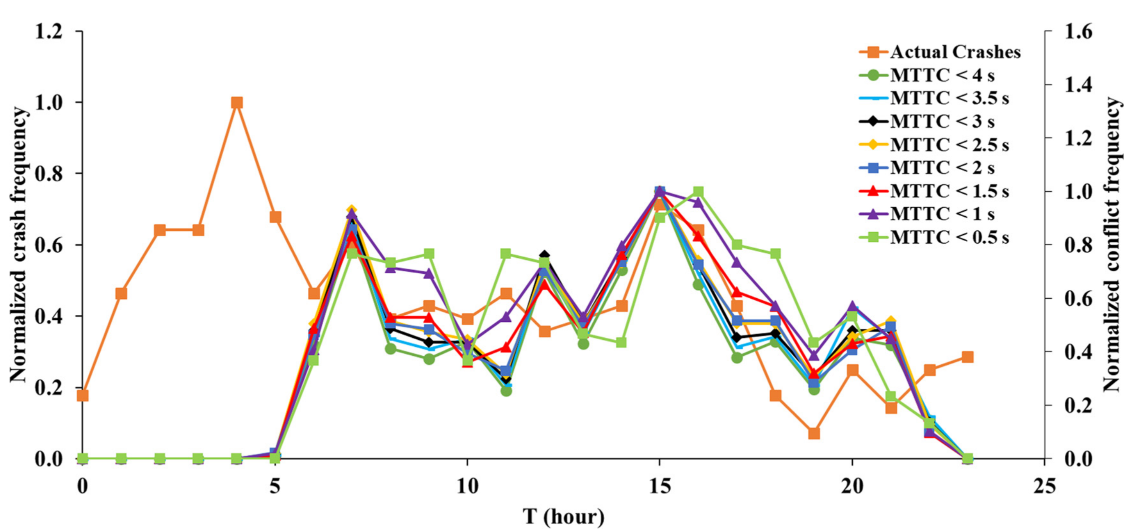

Fig. 6. Comparison of normalized hourly real crash and estimated conflict frequencies.

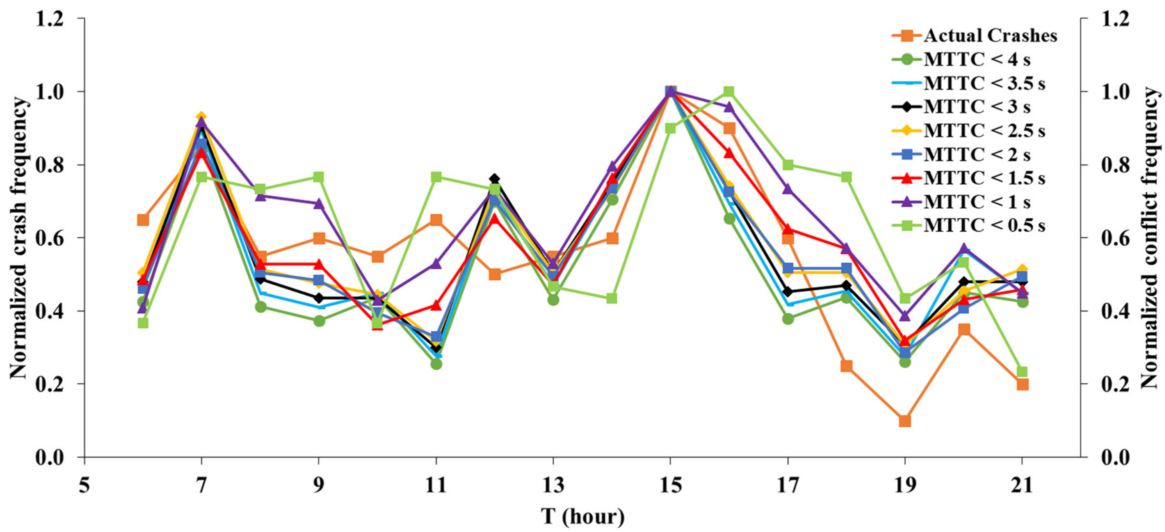

Fig. 7. Comparison of normalized hourly real crash and estimated conflict frequencies for 06:00 h to 22:00 h.

Table 2
Correlation between real crashes and estimated conflicts for different thresholds.

MTTC threshold (s)	Pearson correlation		Spearman rank correlation	
	CC	*p*-Value	CC	*p*-Value
4.0	0.646	0.007	0.324	0.221
3.5	0.627	0.009	0.352	0.181
3.0	0.651	0.006	0.422	0.103
2.5	0.698	0.003	0.518	0.040
2.0	0.668	0.005	0.490	0.054
1.5	0.727	0.001	0.568	0.022
1.0	**0.758**	**0.001**	**0.646**	**0.007**
0.5	0.688	0.003	0.604	0.013

nighttime because of other factors such as low visibility, sleepiness, glare, etc. (Bella et al., 2014). These results are in agreement with the results obtained by Ozbay et al. (2008) who also could not estimate conflicts during nighttime. Hence, it can be inferred that to estimate conflicts during nighttime, specific surrogate measures that can estimate conflicts based on these nighttime factors need to be developed.

5.4.3. Relation between traffic volume, estimated conflicts, and real crashes

To understand the relationship between traffic volume and crashes, traffic volume, estimated conflict frequencies, and real crash frequencies were compared with the time of the day (Fig. 9). It was observed that the estimated conflicts depend on the traffic volume. However, there are large discrepancies between the actual crashes and the estimated conflicts during night time. It may be noted that the conflicts are estimated based on MTTC, which considers only the intervehicular characteristics. These can be estimated only when there is interaction among vehicles. During daytime, because of considerable traffic volume, there is increased interaction between vehicles. In such cases, MTTC becomes successful in estimating conflicts. Thus, it can be inferred that the crashes that occur during daytime are greatly influenced by traffic volume.

5.4.4. Spatial distribution of estimated conflicts and real crashes

The study section was divided into 40 segments of 1 km each to study the spatial correlation between the estimated conflicts and real crashes. This segment length was chosen according to the existing milestones on the expressway. The actual crashes and estimated conflicts were categorized based on the location and time of occurrence of the crash. The geometrical parameters such as gradient and radius of turn were aggregated over each segment and averaged. Table 3 shows the descriptive statistics of the variables under consideration. 'Real crashes' is the independent variable, while the rest are dependent variables. 'Time' is the only categorical variable, while all the others are

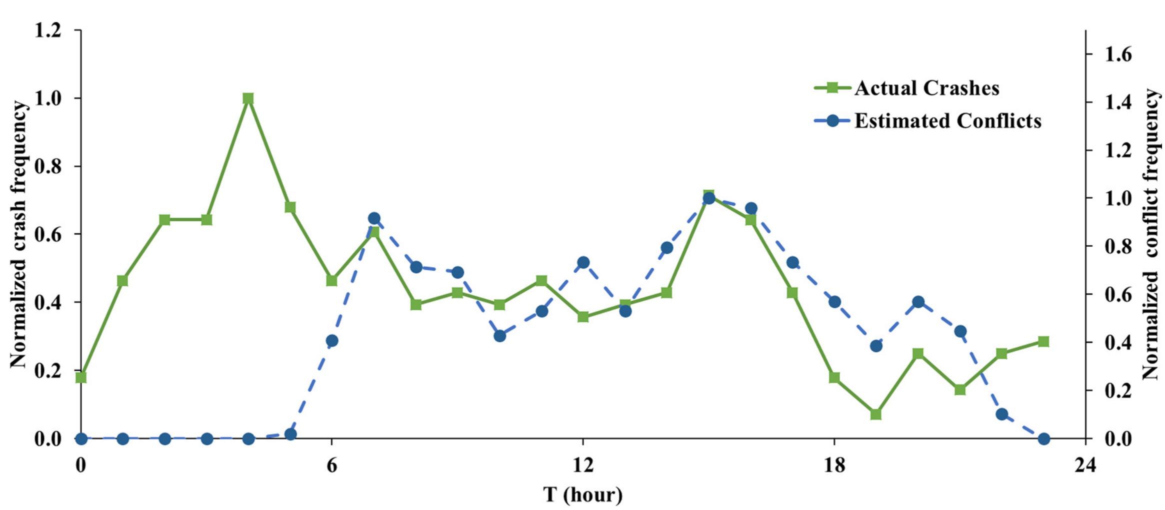

Fig. 8. Time distribution of estimated conflicts and real crashes.

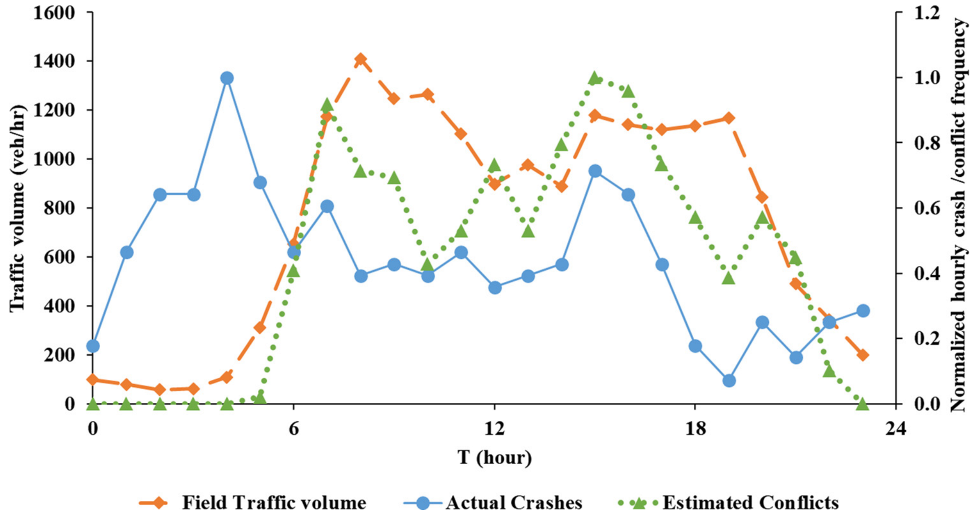

Fig. 9. Comparison of normalized hourly conflict frequency and hourly traffic volume.

Table 3
Descriptive statistics of the variables under consideration.

Variable	Type	Levels	Min.	Max.	Mean	SD
Real crashes (*number*)	Cont.		0	3	0.66	0.86
Estimated conflicts (*number*)	Cont.		0	10	0.81	1.84
Radius of turn (*m*)	Cont.		268	905	759.06	156.33
Gradient (%)	Cont.		−1.77	4.82	0.63	1.54
Time	Cat.	Day Night				

Cont.: continuous; Cat.: categorical; Min.: minimum; Max.: maximum; SD: standard deviation.

continuous variables.

To study the spatial relation between conflicts and crashes a negative binomial model is chosen which can take care of over-dispersion in data and is widely used in crash frequency modeling (Lord and Mannering, 2010; Pande et al., 2017). Independent variables were checked for multicollinearity and only those which do not exhibit multicollinearity have been adopted. Significant variables are identified after several iterations and the final model is presented in Table 4.

The results show that estimated conflicts exhibit a significant correlation (significant at 90% confidence level) with crash data. It can be seen that an increase in estimated conflicts corresponds to an increase in the actual crashes. However, it can also be noticed that the other parameters such as time, the radius of turn, and gradient are less significant in estimating crashes. This could be because the study section consists of mainly straight and flat road segments.

6. Conclusions

This study proposes a generic methodology to estimate conflicts in both lane-based and non-lane-based traffic conditions from vehicle interactions. It identifies critical vehicle interactions based on the precise lateral and longitudinal position of the interacting vehicles and their widths. It then estimates conflicts using the modified time to collision, a widely used surrogate measure of safety. Interactions at every instant for every vehicle in the traffic stream are considered to find even the slight lateral movements which could lead to critical situations.

The proposed methodology was evaluated in lane-based traffic using trajectory data from NGSIM. Comparison of the results with the literature indicates that the proposed methodology is adequate to estimate conflicts for the lane-based traffic conditions. In addition, for the first time, an evaluation is done for non-lane-based traffic condition using the trajectories generated from a calibrated microsimulation model of an expressway. Estimated conflicts were compared with historical crash data over both time and space, and the results show that the estimated daytime conflicts are dependent on the traffic volume. Further, the estimated conflicts show adequate temporal correlation with the crash data for a considerable period of the day. The estimated conflicts also exhibit a significant spatial correlation with crash data. All these results demonstrate the suitability of the proposed methodology for safety evaluation of lane-based as well as non-lane-based traffic, especially for the latter.

However, the results also showed that conflict estimation using MTTC is not sufficient for night traffic. This is probably due to the limitations of MTTC to account for specific parameters such as driver distraction, drowsiness, and visibility influencing the nighttime crashes. Since road safety is essential irrespective of the time of the day, all the influencing factors need to be incorporated while computing the time to collision.

The performance of the methodology can be improved by custom calibration of the microsimulation model for the traffic facility under consideration. Incorporation of environmental parameters in the microsimulation is also expected to further enhance the results. Historical crash data is used for comparison under the assumption that the traffic conditions remain the same throughout. The proposed methodology may be extended to include driver behavior parameters for better prediction of nighttime conflicts.

Table 4
Negative binomial model results.

Parameter	Estimate	Std. error	Wald chi-square	*p*-Value
Intercept	−0.539	0.164	10.76	0.001
Estimated conflicts	0.122	0.064	3.653	0.056
Dispersion	0.135			
Akaike's information criterion (AIC)	178.467			

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