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RECKONING LEVEL OF RISK AND SEVERITY (LORS) BASED ON THE GAP ACCEPTANCE AT A THREE-LEGGED UNCONTROLLED INTERSECTION OF A RURAL HIGHWAY

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Resume

Traffic safety assessment is an essential part of traffic planning and engineering. At uncontrolled intersections, the severity of crashes has increased manifolds. This is due to the fact of not following the priority rule during the right-turning movements. In conventional methods, past accident records were used to analyze traffic safety. However, the drawbacks of the traditional method to estimate the severity require a lot of accident data for analysis to draw any conclusion and suggest safety measures. The accuracy of the record of accidents and details is highly uncertain. Therefore, surrogate safety measures are being used to analyze the safety. In the present paper, the gap acceptance time (GT) is used to examine the risk and the speed and gap values define the level of risk and severity (LORS). Moreover, using the value of the critical gap, the probability of risk is estimated. Further, the level of risk and severity is computed based on the gap and speed data of vehicles at an uncontrolled intersection. Hence, with the speed and gap data, the level of risk and severity is classified as low risk, high risk and low severe, and high severe. The methodology implemented is validated by using the actual accident data.

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1 Introduction

Traffic accidents on the road are one of the major causes of injuries, death, and property loss. Road traffic crashes lead to approximately 1.25 million death of people every year. The statistics show that traffic accidents caused an average of 65123 loss of life and 25540 got injuries as per WHO (World Health Organisation, 2018). Road traffic safety is to be considered first, then to take economic factors into justification. In the case of an accident and prevention, the administrative authority needs to take into account the safety aspect [1]. While designing the road infrastructure the real situation adaptation, based on current trends and development, needs to be considered to respond according to the traffic intensity. The development of the traffic situation is dynamic, difficult to predict, and influenced by several traffic, geometrical and other factors [2]. To improve the functioning of road safety, the context of

the overall road traffic safety management system needs to be considered, which contributes to the complex institutional structure involving the authorities that supports the task and process involved to prevent and reduce road traffic accidents [3]. The other major problem identified is to determine the effect of the system on the technical inspection of vehicles to reduce the accident-related studies examined. However, the effect of technical inspection reduced the accident rates in different countries is investigated and summarised [4]. One of the research studies in New Zealand has reduced to no accidents after the application of the vehicle system investigation [5]. The roadside technical inspection analysis examines the possible impact on transport and logistic system, which has not been explored yet. Hence the effectiveness of inspections on the roadside has an impact on road safety, as well [6].

One of the traditional ways to improve road safety is to analyze the crash data and identify the primary

factors affecting road accident severity. The accident severity does not happen by chance, as different forms can be forecast and prevented. However, the accident analysis has its limitation regarding the data adequacy and quality from the historical records. Therefore, the analysis of the accident prediction and its severity has drawn the attention of researchers for traffic safety, whereas, accidental events can be analyzed by different techniques and can be avoided [7]. The three common ways to obtain the conflicting data are i) field observation, ii) computer simulation and iii) real driving scenario. In the case of actual driving, the driver's behavior, traffic, and environmental characteristics are taken into consideration. Similar to naturalistic driving, a computer simulator will work on the driving behavior and trajectory of vehicles on the field. Moreover, a computer simulator can be an alternative approach to predicting traffic conflict using machine learning techniques. At present, the availability of a large dataset enables to predict the accidents using machine learning as compared to the traditional statistical approach [8]. In the past two decades, several researchers have worked on the severity prediction of traffic accidents based on past hypothetical data and identified the main factors impacting the severity of accidents. In many countries, a significant reduction in fatal accidents is achieved by adopting a holistic road traffic system. In this approach, all the aspects of the road system, which contribute to traffic accidents are considered. But the decisive here is the recognition that there are limits to human activity, which is the gap acceptance behavior [9-10]. Various studies have shown that the driver's behavior has a major impact on accidents. Even the personality and impulsivity of the driver plays a major contribution to road safety [11-13]. Personality traits directly influence the risky behavior of drivers when external factors do not have a direct impact [14-15].

In the past, various researchers used different surrogate safety measures to assess traffic safety. Gap acceptance (GT), deceleration time (DT), time to collision (TTC), and post-encroachment time (PET) are some

commonly used traffic safety surrogate measures [16-17]. On the other hand, PET is one of the most widely used and reliable methods for analyzing traffic safety. The PET is a surrogate safety measure used to identify cases in which two road users pass over a common spatial point or area at a different time [18-19]. PET is the time difference between the first vehicle's exit from the conflict spot and the second vehicle's arrival/entry at the conflict spots. A lower PET value indicates a higher likelihood of collision [18]. One of the research studied the microscopic decision model for the driver's gap acceptance behaviour when waiting at an uncontrolled intersection on a minor road. This model evaluated the risk associated with not accepting the small gaps and the potential benefit of their acceptance [20]. From past studies, it is observed that the gap time is one of the measures of surrogate safety. The estimation of the critical gap enables the prediction of the risk probability and severity. However, there is a lack of research in a similar area and this motivates authors to estimate the level of risk and severity (LORS) and to enhance the safety at unsignalled intersections using the gap time concept. To achieve the objective, the critical gap is estimated using a probabilistic approach and the risk is computed for the vehicle types and right-turning movements [21]. However, there is a lack of research observed for the intersection owing to the unavailability of crash data or past accident records, which are unable to study the severity prediction accurately. Hence, the present paper aims to evaluate the severity and categorize it based on the gap acceptance parameter and conflicting speed of the vehicle. To validate the severity levels, the data of the actual crashes, which have already occurred at uncontrolled T- intersections, is extracted and analyzed.

2 Data collection and processing

Traffic data was collected using videography for six different locations at uncontrolled T-intersections of



Figure 1 Snapshots of the study locations

Table 1 Road inventory details for the study area

Location	L-1	L-2	L-3	L-4	L-5	L-6
Area	Nadiad (Gujarat)	Anand (Gujarat)	Kalol (Gujarat)	Mehmdavad (Gujarat)	Thandla (Madhya Pradesh)	Peeth (Rajasthan)
State Highway Number	SH-12	SH-83	SH-5	SH-3	SH-39A	SH-91
Characteristics of Major and Minor Road	4-lane divided 2-lane undivided	4-lane divided 2-lane undivided	4-lane divided 2-lane undivided	4-lane undivided 2-lane undivided	2-lane undivided 2-lane undivided	2-lane undivided 2-lane undivided
Width of Major Road (in m)	15	15	17.5	12.5	15	14.5
Width of Minor Road (in m)	10.5	10.5	7.5	6.5	6.6	6.0
Stretch Length (in m)	28	30	50	32	28	26
Width of Conflict Area(m ²)	16 x 20	16.6 x 14	18 x 20	14.5 x 12.5	6.6 x 14.5	5.8 x 14.0
85 th Percentile Speed (in kmph)	67	69	75	72	62	57
Peak Hour Volume(PCU/ hr)	2024	2146	2750	2725	610	765
Proportion of 2W (%)	62.66	52.03	50.32	58.10	63.75	73.98
Proportion of 3W (%)	16.21	13.99	5.55	12.63	4.64	4.91
Proportion of 4W (%)	17.05	27.88	29.30	22.37	14.63	15.89
Proportion of LCV (%)	2.81	3.96	6.41	1.35	6.53	2.50
Proportion of Bus (%)	0.88	0.62	2.06	1.27	3.64	1.44
Proportion of Truck (%)	0.38	1.50	6.33	4.25	6.78	1.95

rural highways. The videography was done under the fair-weather condition using a high-definition camera. The camera is placed at a vantage point to avoid disturbance in the driving behavior and obtain the actual driving pattern. The location of the camera is selected in such a way that all three movements are covered to extract the other traffic parameters later on. The physical dimension was evaluated from the field and further used for the analysis. The snapshots of the six locations in the study area are shown in Figure 1.

The road inventory details of the study area including the road geometric features, traffic components, and locations are described in Table 1.

a) Gap data extraction

The gaps were measured in 1/100th of a second, which resulted in a total of 2150 (both accepted and rejected) gaps for major and minor right-turning movements. The summary of the traffic proportion at all the intersections and mode-wise share is shown in Table 1. As it is clear that the major proportion is observed for the two-wheelers whereas a small proportion is recorded for heavy vehicles (bus, truck, and LCV). For all the intersections, the two-wheeler proportion varies from 50% to 73%. Further, the gap in acceptance of the right turning movements - from the major and minor approaches is the focus of this study.

The recorded video was played repeatedly to extract

the data. The data extraction process was conducted manually and recorded the gap (accepted/rejected), vehicle speed, and classified traffic volume count. In Figure 2(a), C1 and C2 are the leading and following vehicles used to calculate the gap time. The stretch length defined in the figure is for calculating the approach speed of the vehicles. It is estimated using the time taken to cross the stretch length, which is marked on the site during videography and the length of the section is presented in Table 1. The occupancy time of the vehicle is extracted manually by calculating the time taken by the vehicle to cross the conflict area. The gap data is extracted for the major and minor right turn for each location. The gap is estimated as a time headway between the two successive vehicles for major and minor streams. The gap data is used for further analysis and therefore its statistics are described in the next section.

b) Descriptive statistics of accepted gap

The descriptive statistics of the gap accepted are elaborated in Table 2. It shows the minimum, maximum values, mean and standard deviation accepted for each location. From Table 2, it is a piece of clear evidence that the minimum value of the accepted gap shows negligible variation for all the locations, whereas the least standard deviation was observed for location 6 and in contrast, the highest standard deviation was observed for location 1.

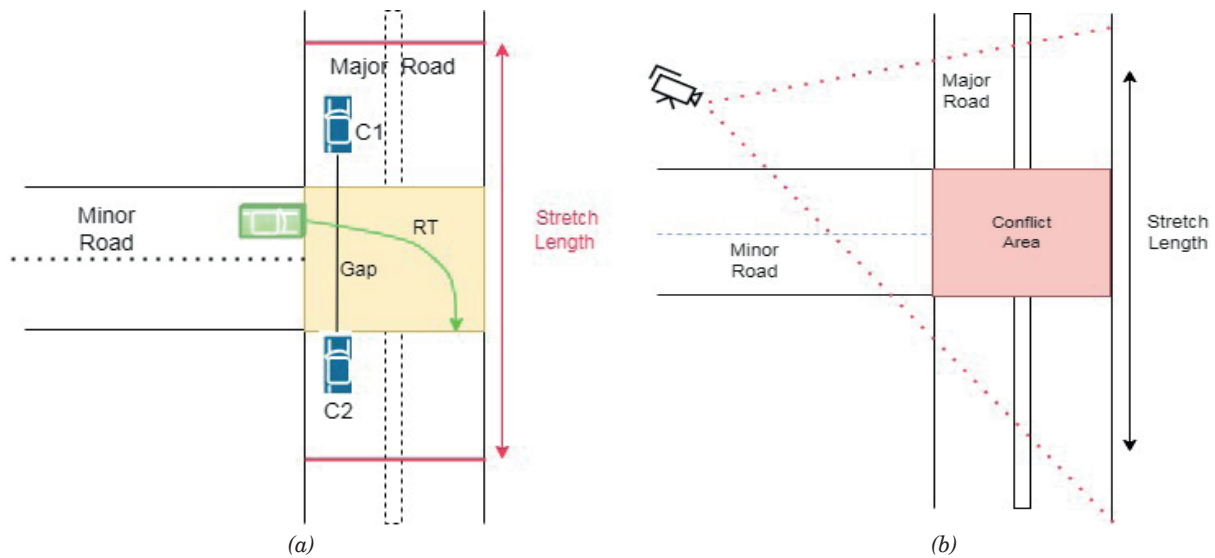


Figure 2 (a) Data extraction methodology and (b) Position of the camera

Table 2 Descriptive Statistics for the accepted gap for each location

	L-1	L-2	L-3	L-4	L-5	L-6
N	269	258	263	135	123	144
Mean	3.08	3.02	3.20	2.08	2.19	1.78
Minimum	1.06	1.09	1.45	1.02	1.03	1.02
Maximum	7.65	8.63	7.72	6.42	6.32	3.63
Variance	1.96	1.64	1.35	0.73	1.16	0.25
Stand Dev	1.40	1.28	1.16	0.86	0.99	0.50

Further, the extracted accepted gaps are used in analyzing and evaluating the critical gap and probability of risk. Figure 3 shows the histogram of the accepted gaps for each location. The different distribution fittings tried to the accepted gap data. The probability distribution functions of gamma, lognormal, Weibull, and General Extreme Value fitted for all the locations are shown in Figure 3. Kolmogorov Smirnov (K-S) test, Anderson-Darling (A-D) test, and chi-square test are used to measure the goodness-of-fit for all the fitted distributions.

The test was performed for different distributions, with a confidence level of 95%, to evaluate each distribution for the accepted gap. Based on the least p-value the best fit of the distribution for each location of the accepted gap is defined.

From Table 3, it is clear that the location-wise distribution is varying as the four distributions- gamma, Weibull, lognormal, and GEV fitted for all the locations. For each location different best fit distribution is obtained considering the least p-value to be the best considering the two-validation test - Anderson darling test and Chi-squared test. The ranking for each location is shown in table 3. However, the most suitable fit is GEV (General Extreme Value) based on the least p-value. Hence, for further analysis, the GEV is considered to estimate the probability of risk (POR). However, it becomes fairly complex to apply the various distributions for the location

and vehicle type-wise to obtain more accurate results. The following section deals with the estimation of the critical gap, using the Binary Logit Model (BLM) and the evaluation of POR using the critical gap value [22].

3 Methodology

The present research work focuses on evaluating the level of risk and severity. The methodology for the current research is briefly shown in the form of a flow diagram in Figure 4.

Figure 4 shows the complete methodology of the research work. The data for the study location is collected and extracted manually to estimate the value of the critical gap. Further, the probability of risk is evaluated to understand the correlation between the gap size and risk. Then, the level of risk, severity, and safety are categorized based on different parameters and the approach. Based on the categorization of risk, severity, and safety level, LORS is defined and categorized under three categories. To validate the approach, the actual accident data of speed and the gap are considered, which is explained in the result and discussion section. As a result, the approach of LORS explained in the current research paper is concluded with positive results. However, each step of the chart is explained in detail in the further sections.

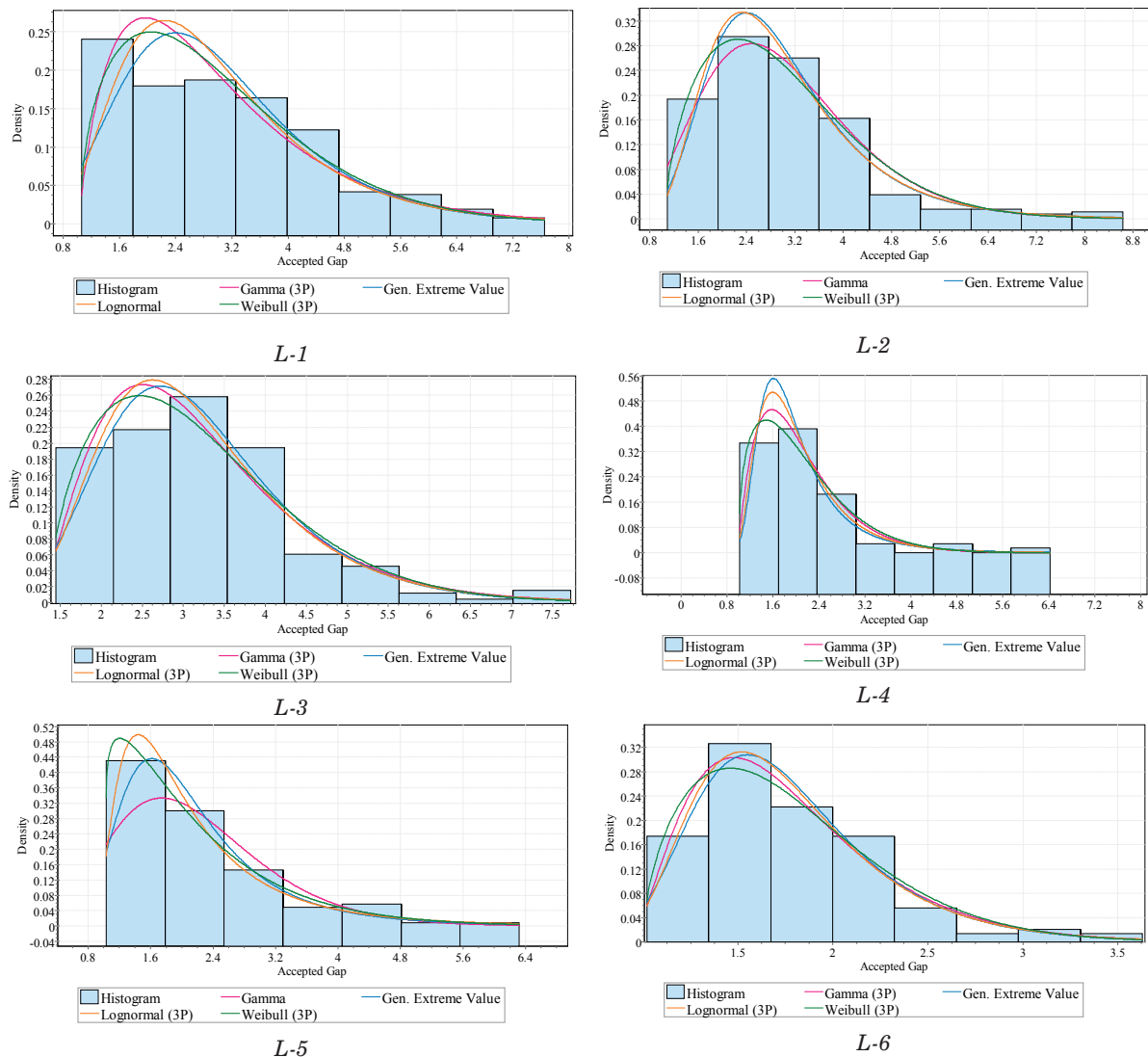


Figure 3 Distribution fitting for accepted gaps for all locations

4 Critical gap estimation

The drivers' decision for the gap, i.e. whether to accept or reject an available gap, was modeled as a function of the gap size, waiting time of the offending vehicle, and speed of the conflicting vehicle in the current study, using the binary logit regression. Table 4 displays the model summary. As the critical gap value is estimated using a probabilistic approach, the influence of traffic and geometrical parameters on that value is taken into account [21].

A negative coefficient for the gap size can be found in all of the models developed in this study. It implies that as the gap widens, the likelihood of rejection decreases or the likelihood of acceptance increases. A similar positive sign for the speed of the opposing vehicle can be observed. This demonstrates that as the speed of the opposing vehicle increases, implies the likelihood of rejecting a gap. There are consistent observations for both crossing movements and different vehicle types.

The occupancy time has a negative coefficient. This means that as the occupancy time increases, so does the likelihood of rejection. This demonstrates, as the occupancy time increases, drivers become impatient and force themselves into the traffic flow by accepting and rolling over smaller gaps to navigate through the intersection. There are consistent observations for both the crossing movements and different vehicle types. The current study aims to estimate the critical gap first and then to estimate the severity levels using the probability of risk considering GEV distribution by the gap-acceptance phenomenon in mixed traffic conditions. Table 5, presents the value of the critical gap for the crossing movements and the type of vehicles estimated using a binary logistic regression model.

The observation for the value of the critical gap is that the two-wheelers and three-wheelers are having a lesser value as compared to the car and heavy vehicles due to the area of the vehicle type. Maneuvering the vehicles with a larger area requires more time to take

Table 3 Goodness of fit value for distribution fitting for each location for an accepted gap

Location	Test	Statistic	Lognormal	Weibull	Gamma	GEV
L1	K-S test	p-value	0.074	0.088	0.072	0.074
		Rank	2	4	1	3
	Anderson Darling Test	p-value	1.814	3.626	1.499	1.669
		Rank	3	4	1	2
	Chi-Squared test	p-value	15.519	15.328	13.221	15.771
		Rank	3	2	1	4
L2	K-S test	p-value	0.041	0.074	0.055	0.040
		Rank	2	4	3	1
	Anderson Darling Test	p-value	0.450	3.7267	1.332	0.458
		Rank	1	4	3	2
	Chi-Squared test	p-value	8.897	9.477	6.831	9.964
		Rank	2	3	1	4
L3	K-S test	p-value	0.047	0.076	0.048	0.044
		Rank	2	4	3	1
	Anderson Darling Test	p-value	0.783	2.7978	0.67578	0.646
		Rank	3	4	2	1
	Chi-Squared test	p-value	17.618	9.072	31.427	20.827
		Rank	2	1	4	3
L4	K-S test	p-value	0.093	0.149	0.120	0.045
		Rank	2	4	3	1
	Anderson Darling Test	p-value	1.460	7.719	4.091	0.357
		Rank	2	4	3	1
	Chi-Squared test	p-value	13.351	19.836	26.184	7.975
		Rank	2	3	4	1
L5	K-S test	p-value	0.090	0.142	0.110	0.068
		Rank	2	4	3	1
	Anderson Darling Test	p-value	1.061	4.025	1.681	0.662
		Rank	2	4	3	1
	Chi-Squared test	p-value	19.278	26.328	17.942	16.850
		Rank	3	4	2	1
L6	K-S test	p-value	0.041	0.095	0.056	0.042
		Rank	1	4	3	2
	Anderson Darling Test	p-value	0.307	2.843	0.703	0.262
		Rank	2	4	3	1
	Chi-Squared test	p-value	1.949	7.871	1.8814	6.533
		Rank	2	4	1	3

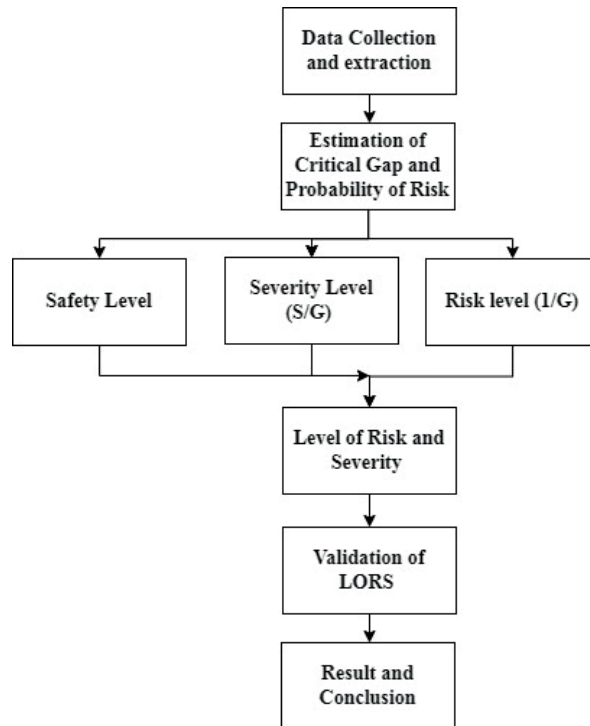
the right turn as compared to the vehicles with a lesser area [23]. Whereas for the crossing movements, major to minor turning vehicles accept the larger gap compared to the minor to major turning vehicles. Hence, the risk for minor right-turning vehicles is larger, which has been demonstrated in further sections.

5 The risk analysis

The accepted gap or rejected gap is the measurement of the decision of the driver for crossing the intersection. The smaller gap is rejected by the driver whereas the larger gap is accepted [21]. Moreover, a similar concept

is applied for both temporal and spatial gaps as only the measurement units are different but the decision of the driver remains the same. When it comes to the matter of the dilemma zone, the spatial gap is in focus, whereas for capacity estimation and delay calculation, the temporal gap plays a crucial role. Hence, a driver accepting a smaller spatial gap sustains more risk as compared to a driver accepting a larger gap. This denotes that the risk (R) is an inverse function of the magnitude of the spatial accepted gap and it can be represented mathematically in the following form:

$$Risk(R) = \frac{1}{Accepted\ gap(s)}. \quad (1)$$

**Figure 4** Research Methodology**Table 4** Coefficient of the model and parameters for estimating the critical gap using a binary logit model

Variables/ Coefficient	Major RT				Minor RT			
	2W	3W	4W	HV	2W	3W	4W	HV
Gap	-0.794	-1.127	-1.02	-0.46	-0.432	-2.19	-1.27	-1.26
Occupancy Time	-0.10	-0.06	-0.02	-0.351	-0.218	-0.074	-0.058	-0.043
Speed	0.017	0.013	0.056	0.051	0.014	0.043	0.064	0.084
Constant	2.649	2.492	0.485	4.078	3.247	3.189	1.66	0.152
Accuracy Prediction	75.7	70.8	63.8	70.0	75.5	74.5	71.4	79.6
Log-likelihood function	533.80	335.89	336.66	139.08	358.50	225.81	231.667	91.65
Cox and Snell R squared	0.274	0.265	0.256	0.176	0.266	0.366	0.246	0.312
Nagelkerke R squared	0.371	0.355	0.341	0.237	0.355	0.488	0.328	0.420

Table 5 Critical Gap (in sec) value using Binary logit model

Location/ Vehicle Type	L1	L2	L3	L4	L5	L6
Major Right-Turn						
2W	2.45	2.92	2.46	2.4	2.39	2.28
3W	2.39	2.43	2.54	2.45	2.44	2.57
4W	3.23	3.57	3.08	2.51	2.93	2.87
HV	4.47	4.18	4.41	3.46	3.55	4.78
Minor Right Turn						
2W	2.31	2.09	2.45	2.06	2.24	2.29
3W	2.35	2.43	2.53	2.22	2.28	2.36
4W	3.27	3.19	3.55	3.33	3.23	3.39
HV	3.55	3.42	3.92	3.44	3.53	3.55

The above equation shows that the greater the value of the accepted gap, the lower the risk, and vice-versa. According to the researcher, the Probability of Critical

Crossing Conflicts (PCCC) is an indicator of operational risk for unsignalised intersections [24]. It is derived using the EVT (Extreme Value Theory) modeling for the

Table 6 Probability of Risk based on critical gap values ($X_1 < \text{Risk} < X_2$)

Location	L1	L2	L3	L4	L5	L6
Major Right-Turn						
2W	72.76	48.44	75.30	38.19	34.91	17.65
3W	75.75	79.92	73.71	25.85	47.61	18.82
4W	59.33	61.52	75.21	45.15	26.41	11.06
HV	65.14	73.78	47.32	25.98	16.71	12.50
Minor Right Turn						
2W	65.04	88.75	76.90	80.01	27.65	31.59
3W	84.02	79.31	77.28	73.18	37.99	33.95
4W	73.21	73.73	55.70	59.42	45.48	25.28
HV	92.29	88.13	67.41	81.73	31.19	18.47

post-encroachment time (PET) data. The current study derives risk probability from a similar concept and is used to estimate level-of-risk and severity (LORS).

Although several researchers have demonstrated that the gap acceptance behavior enables the suggestion of safety measures, there is a lack of research on the probability of risk (POR). Recently, the researchers explained how the EVT can be used to estimate the number of conflicts in a specific section [25-26]. To estimate the POR, the best-fit distribution must be estimated and according to analysis, the GEV distribution is found to be the best-fitted distribution model. Hence, the GEV is used to estimate POR in the present study.

Assume $X_1, X_2, X_3, \dots, X_m$ as independent random variables (in the present case, the value of risk) with a similar probability distribution, where $Y_n = \max(X_1, X_2, X_3, \dots, X_m)$. When $n \rightarrow \infty$, the Y_n will converge to a GEV distribution [27], as shown in Equation (2).

$$f(x) = \frac{1}{\sigma} \exp\left(-\left(1 + kz\right)^{-\frac{1}{k}} \left(1 + kz\right)^{-\frac{1}{k}}\right) \quad k \neq 0, \quad (2)$$

where, $z = (x - \mu)/\sigma$, μ is the location parameter, σ is the scale parameter and k is the shape parameter.

The POR is defined as an area under the probability density function of GEV distribution between the thresholds of the gap representing serious conflicts. The POR can be computed using the following Equation (3).

$$\text{Probability of risk (POR)} = \int_{LL}^{UL} f(x) dx, \quad (3)$$

where $f(x)$ is the probability density function of the GEV distribution, LL and UL represent the Lower and Upper limits of risk, representing critical conflicts, respectively.

Whether the driver chooses to accept or reject a gap within the dilemma zone, will rely on the characteristics of the approaching vehicle (vehicle type and speed), traffic volume, and the traffic control signs at the intersection. Additionally, gender, age, and driving behaviors contribute to the dynamic nature of accepted gaps. Drivers might prefer a wider space over a narrower one. However, given the variety of gaps that are accessible,

a driver can be conflicted about whether to accept or reject a particular gap [28]. Therefore, considering these dynamics in gap-acceptance phenomena, it becomes imperative to arrive at a single gap value, potentially representing the population. Recently, a study reported that spatial critical gaps could characterize the risk of crossing conflicts [29]. Based on the critical gap value, the risk of crossing conflict was characterized as serious and non-serious conflicts. Therefore, the critical gap value was used in the present study to evaluate the POR of the un-signalized T-intersections.

Considering the critical gap as a threshold to define the serious conflict, the equation to estimate the POR can be rewritten as:

$$\text{Probability of risk (POR)} = \int_{\text{minimum risk}}^{\text{risk at critical gap}} f(x) dx. \quad (4)$$

Table 6, shows the probability of risk for the crossing movements and different vehicle types for each location. It can be observed that minor to major right-turning vehicles have a higher probability of risk due to smaller gap-accepting behavior. Moreover, when the vehicles are compared, the heavy vehicles (92%) have the higher risky behaviour, related to the other vehicle types (65 %). The location-wise risky behavior comparison shows that L-6 (11% -33%) is safer as compared to the other locations (25% -92 %). Therefore, it can be determined that the probability of risk of vehicles for the crossing movements is depended on the driver's gap acceptance behavior.

The severity index is a value that indicates the hazardousness of the accidents at road sections, although it can be classified as minor/major injury or fatal depending on the harm to the vehicle and the passenger. In general, the severity index is defined as the ratio of the actual injuries that occurred to the total number of accidents. However, due to the unavailability of the accident data, an alternative approach is used in this paper to estimate the severity level using the gap acceptance behavior of the driver and the speed of the vehicle [17], the severity level is classified using the ratio of the speed to the gap of an individual vehicle; the particular value for the different vehicles is determined

Table 7 Speed to Gap Ratio Value

Location / Vehicle Type	L1	L2	L3	L4	L5	L6
2W	21.60	35.20	23.10	31.05	34.26	20.34
3W	19.17	25.32	19.62	22.82	26.21	21.27
4W	24.65	17.60	21.43	27.06	30.72	18.86
HV	13.12	9.68	10.92	21.58	23.97	18.32

**Figure 5** Average Silhouette value for three clusters in a two-step clustering technique**Table 8** Speed-to-gap ratio classification using various clustering techniques

Clustering Technique	Cluster 1	Cluster 2
K-Mean Clustering	5.38	11.72
Two-step Clustering	5.65	11.85
Hierarchical Clustering	5.62	11.92

for each location.

Table 7, shows values of the speed-to-gap ratio for different vehicle classes and locations. The speed-to-gap ratio is used to classify the threshold for the level of risk and severity.

6 Severity analysis

Clustering is the process of arranging a set of objects belonging to the same group. In the present study, the severity of each gap is computed and clustered using different techniques. The three-clustering methods were used, namely - two-step clustering, k-mean clustering, and hierarchical clustering.

In Figure 5, the average silhouette for two clusters for the two-step clustering is shown, where two-clustering is having fair results for the quality of the cluster. Due to the following results, the clustering is done under two categories, as for one and three clustering the quality of the model has decreased to poor. Hence, the two clusters are developed using the three different clustering techniques.

Table 8 shows the results of the clustering by three different methods. It can be observed from the table itself that the variation of the values does not vary much. For classifying it into clusters the lower value

is considered. As the value is considered for the safety purpose the lower value if considered, will be safe for the higher value as well.

Table 9, presents the risk calculated based on the reciprocal of the accepted gap and to normalize the value, a critical gap value is used. The speed-to-gap ratio is classified based on the clustering techniques. The combination of both the gap-to-critical gap ratio and the speed-to-gap ratio is utilized to identify the level of risk and severity respectively. The HRHS, i.e. High-Risk High Severity is defined as the value of risk less than 1 and the speed-to-gap ratio greater than 11.72. The other term, i.e. HRLS - High-Risk Low Severity is where the value of risk is less than or equal to 1 and the speed-to-gap ratio is between 5.38 to 11.72; lastly, the LRLS - Low-Risk Low Severity is where the value of the risk is greater than 1 and the speed to gap ratio is less than 5.38. This concept is developed based on the practical considerations that if the gap and critical gap ratio were less than 1, the driver's behaviour is riskier. On the other hand, if the ratio is greater than 1 means that drivers perceive less risky behavior. Hence, the complete analysis is done based on the concept of the high and low risk and severity, which is further correlated with safety for ease of understanding and validating the approach.

The level of safety is categorized as safe, which means that it does not have any probability of conflict.

Table 9 Classification of risk, severity, and safety based on speed and gap parameter

G/CG	Level of Risk	S/G	Level of Severity	Classification of Crash	Level of Safety
<1	High Risk (HR)	>11.72	High Severe (HS)	Demise	Fatal (HRHS)
<=1	High Risk (HR)	<5.38	Low Severe (LS)	Major Injury	Highly unsafe(HRLS)
>1	Low Risk (LR)	<5.38	Low Severe (LS)	Minor Injury	Unsafe (LRLS)

*G/CG: Gap to Critical gap and S/G: Speed to Gap Ratio

*Car-Truck (Fatal)**LCV- Car (Highly Unsafe)**Car- Bus(Fatal)**LCV- Car (Highly Unsafe)***Figure 6** Few snapshots of the actual accidents that occurred at an uncontrolled three-legged intersection

Unsafe shows that the probability of conflict is greater, but the injury to the passenger or driver is negligible or had a minor injury, whereas highly unsafe means major injury to the passenger or a driver and severe destruction to the vehicle/s. A fatal or disastrous accident means that there is a demise of one or more people due to the conflict and vehicles are damaged entirely. All the categories shown in Table 9, for the safety or level of risk and severity (LORS), are defined above.

7 Result and discussion

The number of crashes at the uncontrolled intersection is increasing, but the record of the actual accidents is not readily available with the details. Hence, this study has moved forward a step, to observe the severity level of actual accidents that have already occurred at an uncontrolled intersection. Moreover, this evaluation of accidents also enables for the validation of the above level of risk and safety, based on the speed and gap data. Therefore, to validate the severity and risk levels, the accidents are evaluated using an open-source video (YouTube videos). Table 10, denotes the validation

of the severity and risk levels using the data (speed and gap) of actual accidents that occur at a similar type of intersection for the different vehicle types. Capturing the actual accidents is a quite tough task, but still, some data was available, which is used to validate the approach.

A few images of the crashes are shown in Figure 6. The videos are played repeatedly to obtain the value of the gap and the speed is calculated by the time taken to cross a particular stretch and distance is extracted from the video. Hence, the speed of the vehicle is calculated and used for further analysis to estimate the speed-to-gap ratio. The level of safety of the accident is observed under three categories- unsafe, highly unsafe, and fatal. However, the predicted LORS is based on the speed and gap value, whereas the observed LORS (level of safety) is estimated based on the actual accident scenario from the open-source video. Further, the observed and predicted LORS is compared and the detailed analysis is discussed in Table 10.

Table 10, shows the crashes that occurred by the vehicle type, gap time, speed of the conflicting vehicle, critical gap (estimated using BLRM), predicted LORS, and observed LORS of the accidents. The prediction

Table 10 Actual accident data validation with the predicted severity level

Vehicle Type	Gap (s)	Speed (kmph)	Critical Gap (s) (Calculated using BLRM)	Risk = G/CG	Speed / Gap	Predicted LORS (from S/G and AG/CG)	Observed LORS (from video)
M2W	3.98	25.25	1.63	2.44	6.34	LRLS	LRLS
M2W	3.4	22.48	1.78	1.91	6.61	LRLS	HRLS
M2W	1.76	34.85	2.97	0.59	19.80	HRHS	HRHS
M2W	2.53	35.45	3.08	0.82	14.01	HRHS	HRHS
M2W	2.49	28.62	2.81	0.89	11.49	HRHS	HRHS
M2W	2.11	22.15	3.41	0.62	10.50	HRHS	HRHS
M2W	1.69	32.46	3.31	0.51	19.21	HRHS	LRLS
M2W	2.23	25.62	4.13	0.54	11.49	HRHS	HRHS
M2W	3.39	28.15	2.87	1.18	8.30	LRLS	HRHS
M2W	1.63	32.48	3.81	0.43	19.93	HRHS	HRHS
M3W	2.56	24.62	3.02	0.85	9.62	HRHS	LRLS
Car	2.13	39.45	2.56	0.83	18.52	HRHS	HRHS
Car	2.63	33.26	3.04	0.87	12.65	HRHS	HRLS
Car	1.84	45.89	3.54	0.52	24.94	HRHS	HRHS
Car	3.97	30.25	2.83	1.40	7.62	LRLS	LRLS
Car	2.42	45.23	4.28	0.57	18.69	HRHS	LRLS
HV	3.45	32.68	2.6	1.33	9.47	LRLS	HRLS
HV	2.81	45.18	3.68	0.76	16.08	HRHS	HRHS
HV	2.27	35.84	3.33	0.68	15.79	HRHS	HRLS
HV	2.44	42.15	3.67	0.66	17.27	HRHS	HRLS
HV	3.7	32.45	3.68	1.01	8.77	LRLS	LRLS
HV	3.11	28.46	2.76	1.13	9.15	LRLS	LRLS
HV	3.5	25.15	2.16	1.62	7.19	LRLS	LRLS
HV	2.36	36.87	3.35	0.70	15.62	HRHS	LRLS
HV	3.32	35.48	3.44	0.97	10.69	HRHS	LRLS
HV	3.09	25.86	4.15	0.74	8.37	HRHS	HRLS
HV	2.54	32.15	4.59	0.55	12.66	HRHS	LRLS
HV	2.05	32.54	4.04	0.51	15.87	HRHS	HRLS

Note: HRHS- High-Risk High Severity (fatal), HRLS- High-Risk Low Severity (highly unsafe), LRLS- Low-Risk Low Severity(Unsafe)

accuracy of the approach is evaluated based on the observed and the predicted LORS. If the observed and predicted value were the same for a particular accident the crash prediction accuracy is considered 100% whereas, if either risk or severity is predicted accurately then it is considered to be 50% accurate. Moreover, if the predicted and observed value does not match, then it is considered to be 0. Therefore, the average accuracy prediction for the observed and the predicted level of severity comes to 66.07%. This approach can further be modified to enhance prediction accuracy by acquiring more crash details and records. Last but not the least, the observations and the predictions done in the present study are the initial approach to increase safety. The uniqueness of this research is that the actual accidents are used to validate the results. The accuracy percentage of the approach gives fair results and that can be modified by getting more data.

Hence, it can be presumed that the risk and severity level estimated enables in the reduction of the severity of accidents. The prediction of the level of risk and severity (LORS) is evaluated based on the speed and gap acceptance behavior of the driver for different vehicle types at right-turning movements.

From Figure 7, the LORS can be classified as HRHS, HRLS, and LRLS depending on the accepted gap and speed parameter. In the graph, the X- axis denotes the G/CG - gap to the critical gap ratio, which defines the level of risk. If the ratio is less than 1, it is less risky and a ratio greater than 1 perceives higher risk. Moreover, the Y-axis denotes the level of severity based on the speed-to-gap ratio, values greater than 5.38 and lesser than 11.72 define low severity and a ratio greater than 11.72 defines high severity. Hence, the combination of the risk and severity levels enables the delineation of the LORS. Based on the LORS, remedial measures can be suggested

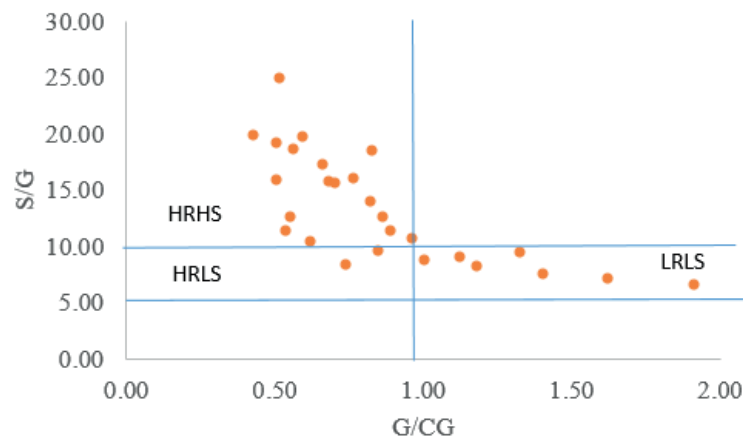


Figure 7 Level of Risk and Severity based on Speed and Gap Value

Table 11 Remedial measures based on LORS

G/CG (Risk)	S/G (Severity)	LORS	Remedial Measures
<1	>11.72	HRHS	ADAS (Advanced Driver Assistance System)
<=1	<5.38	HRLS	Road Markings
>1	<5.38	LRLS	Stop Signal

to reduce the severity of crashes at uncontrolled three-legged intersections. As per LORS, a few measures that can be suggested are presented in Table 11.

Table 11, deliberated the safety measures that can be implemented in the existing intersection to reduce the severity of accidents based on LORS. As the LORS is identified on the gap acceptance parameter and speed of a vehicle, the safety measures are suggested on similar parameters. Moreover, this study can further be extended for different types of intersections with varying geometrical and traffic characteristics.

8 Conclusion

Traffic movements at an uncontrolled three-legged intersection are highly complex. The high speed at the intersection is one of the attributes of conflicts at the right-turning movements. This complex right-turning manoeuvre increases the risk of collision and creates a threat to safety for both offending and conflicting vehicle types. Various measures are available to analyze traffic safety, out of which the gap time is used in the present paper. This study calculates the gap size and estimates the critical gap and probability of risk, which is further used to evaluate the level of risk and severity.

The classified level of risk and severity, obtained from the actual accident data that occurred at similar types of intersections are validated. The ratio of speed to the gap is used to classify the level of severity, which gave two thresholds of 5.38 and 11.72 after using the clustering technique. Additionally, the ratio of the gap to the critical gap was used to classify the driver's risky

behavior in the section. If the ratio was less than 1; it denotes the risky behavior of the driver. Moreover, if the ratio is greater than or equal to 1; the driver perceives less risky behavior. Hence, the LORS is categorized as HRHS, HRLS, and LRLS. The actual conflicts at the three-legged uncontrolled intersections are acquired by the open-source video. The data for speed and gap are extracted and the LORS is estimated based on the data, i.e. the predicted LORS. The level of safety is observed, which is further correlated with the LORS (observed LORS). In comparison, the accuracy percentage for the approach was found to be 66.07%. Based on the severity of crashes observed, suitable remedial measures can be implemented to reduce the severity of accidents at unsignalled intersections on rural highways. The value of the gap and the speed of a vehicle can be used to categorize the level of risk and severity (LORS). This analysis can be further extended for estimating the level of risk and severity for each vehicle type and different road sections.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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