CHAPTER

11

Surrogate safety measures

11.1 Introduction

Traffic crashes are a direct and therefore ideal measure of road safety. However, obtaining crash data may present a challenge due to their availabilility and quality issues. Additionally, rare types of crashes (e.g., those involving pedestrians and bicyclists) yield small sample sizes that can result in inconclusive or unreliable crash-based safety evaluations. Besides data availability and quality, the evaluation of new safety treatments also presents a challenge, as it can take years and multiple installations to obtain sufficient observations. The Highway Safety Manual (HSM) (AASHTO, 2010) provides methodological approaches to calculating the expected annual average crashes given a set of variables, but their applications are hindered by a lack of quality and detailed roadway and traffic data as well as issues related to model transferability and calibration.

The challenges associated with crash-based analyses have driven the development of surrogate safety measures. The word "surrogate" is used because the measures are based not on crashes but on traffic conflicts, which are defined as the occurrence of evasive vehicular actions and often characterized by braking and/or weaving maneuvers. Surrogate safety measures have several different forms and definitions, with traffic conflict as being the most widely used and perhaps, the most consistent one. Surrogate safety measures support the rapid evaluation of innovative intersection designs and traffic control strategies without waiting for a crash history, diagnose specific safety concerns to proactively identify solutions, and gather a large sample size for rare crash types in a short time.

However, measuring safety surrogates is not as definitive as it sounds. Issues associated with surrogate safety measures include the following: (1) varying performances by different algorithmic approaches to measuring road safety; (2) determining the threshold values that can affect the

https://doi.org/10.1016/B978-0-12-816818-9.00018-4

outcome of conflict-based safety studies; and, (3) validating the correlation between conflicts and crashes. Over the past 5 decades, substantial efforts have been devoted to designing state-of-the-practice traffic conflicts techniques and developing surrogate measures to address a wide range of road safety issues. Nevertheless, the lack of rigorous theories that support traffic conflicts as the basis of crash prediction and the inconsistency among conflict measures affect users' confidence.

This chapter focuses on defining, analyzing, comparing, and applying state-of-the-art surrogate safety measures. Following a brief history of traffic conflicts, readers learn about the traffic conflicts technique (TCT) and the practice of observing and collecting traffic conflicts in the field. Next, both the pragmatic approach and the theoretical development of surrogate safety measures are explored. The practical approach section includes an introduction and discussion of temporal- and spatial-based proximity safety indicators. The theoretical section introduces the concept of safety hierarchy and statistical models from the extreme value theory.

11.2 An historical perspective

Traffic conflicts were defined as events such as "*a driver takes evasive action, brakes or weaves to avoid a collision*" (Perkins and Harris, 1967). The TCT procedure was conceived as a systemic approach for observing and measuring crash potential. Since then, TCT has gained popularity as a diagnostic tool used to determine appropriate safety countermeasures at high crash locations and as an evaluative tool for safety treatments.

Over the years, undesirable characteristics have been reported regarding this measurement's dependency on the observation of evasive actions. Pragmatic questions have been raised, such as: Can we exhaust all possible evasive actions? How can an evasive action be characterized (e.g., deceleration or acceleration)? Is the instance and intensity of an evasive action the only way to measure the severity of conflict? Can traffic conflicts be used to predict crashes that might occur in a particular year or to estimate an expected average number of annual crashes, provided that crashes are random events?

Real-world experience tells us that evasive actions alone may not be adequate in indicating a hazardous situation, as crashes come from either failed evasive maneuvers or no evasive maneuvers at all (Allen et al., 1978; Glauz and Migletz, 1980; Chin and Quek, 1997). Hayward, in his 1971 doctoral dissertation titled "*Near misses as a measure of safety at urban intersection*," suggested using the time measured to collision—the first indicator based on proximity to a crash in time—to judge the severity of near-miss cases (Hayward, 1971). The research on such measures of safety flourished after Hayward's dissertation. Many safety indicators were introduced at the first workshop on traffic conflicts in Oslo, Norway in 1977 (Oslo, 1977), including a more inclusive and unified definition of traffic conflicts: "*An observable situation in which two or more road users approach each other in time and space for such an extent that there is risk of collision if their movements remain unchanged*" (Amundsen and Hyden, 1977).

The 1977 definition of traffic conflicts is more of a principle that has guided the development of many practical measures to quantify the extent of proximity, widely called as surrogate safety measures. Time-based proximal indicators are the most popular because they integrate both distance and speed. Safe stopping distance, the proportion of stopping distance, and decelerate rate-based measurements have also been proposed. Readers can refer to several review papers for a comprehensive overview and discussion of surrogate measures of safety (Chin and Quek, 1997; Zheng et al., 2014a,b; Mahmud, et al., 2017; Johnsson et al., 2018).

On the frontier of developing basic theories that underpin the surrogate safety measures, considerable research has been dedicated to rationalizing the relationship between observable noncollision events and crashes, either on a scale of nearness to a collision (Glauz and Migletz, 1980) or in a hierarchical structure such as a safety pyramid (Hyden, 1987). Both concepts are based on the notion that conflicts must precede collisions, irrespective of the evasive actions, and conflicts are more frequently observed but are less severe than collisions. Extreme value models have emerged as the leading method for modeling rare and extreme events such as crashes (Songchitruksa and Tarko, 2006; Tarko, 2012).

Recent efforts have been directed toward modeling the complex behaviors of road users because the type of evasive action a driver might take at that moment is unknown. A holistic view of the possible maneuver taken by the driver at the current position and state is more appropriate to assess the imminent collision he or she may encounter. Saunier and Sayed (2008) have suggested considering all possible options for road users during the encounter. For example, the collision probability for a given interaction between road users is the sum of the collision probability over all possible actions (e.g., acceleration, deceleration, change direction, do nothing) leading to a collision. Ismail et al. (2011) have proposed a comprehensive safety index that integrates various sets of measures with different aspects of conflicts. Recently, Zheng and Sayed (2019) have developed bivariate extreme value models to jointly model two traffic conflicts indicators: time to collision (TTC) and post encroachment time (PET) and obtained improved crash estimation accuracy and precision. With the arrival of new data and technologies, the theory of surrogate safety measures continues to evolve at a fast pace as a prominent method for proactively identifying safety concerns and deficiencies.

11.3 Traffic conflicts technique

Since its inception in 1967, the TCT has been well received and adopted by many traffic engineers and safety professionals as a tool to measure the severity of conflict and to recommend corrective actions for crash prevention. In 1989, Federal Highway Administration (FHWA) published the guide titled *"Traffic Conflict Techniques for Safety and Operations"* to standardize the collection and analysis of traffic conflicts (Parker Jr. and Zegeer, 1989). The federal report includes an engineer's guide and an observer's manual. The engineer's guide provides basic background information and standard procedures for using traffic conflicts to analyze safety and operational problems at signalized and unsignalized intersections and to make decisions and recommendations for improvements. The observer's manual provides basic background information and step-by-step instructions for conducting traffic conflict surveys in the field.

According to the observer's manual, to qualify as a traffic conflict, the action of the first user must place the other user on a path toward collision and the other user must take an evasive maneuver such as braking or swerving to avoid the collision. The general definition of traffic conflicts extends to the near misses and collisions when the other user is either unaware of the collision potential or has poor judgment and does not make an evasive maneuver, or when the evasive action is inadequate or inappropriate for conditions. The general definition excludes red-light violations, or the conflicts that result from traffic violations, which is a remarkable difference from the General Motors Research Laboratory (GMR) TCTs. However, traffic violations can be counted as traffic conflicts in certain situations, such as when a red-light running camera is being evaluated.

The observer's manual breaks down the process of a conflict into four stages: (1) the first vehicle makes a move that starts an encroachment (e.g., starting a left-turn movement from an exclusive left-turn lane); (2) a second vehicle is placed in danger of a collision; (3) the driver of the second vehicle sensing danger reacts by taking an evasive action (i.e., braking or swerving); and (4) the second vehicle continues to proceed through the intersection. The four stages outline a clear sequence of key moments for measurement boundaries.

The manual also recommends using a traffic conflict survey to: (1) count conflicts by type and observe safety-related traffic events; (2) answer questions about safety and operational problems; (3) recommend corrective treatments; (4) demonstrate the effectiveness of improvements; (5) supplement crash data analysis, signal warrants studies, capacity analysis, and other engineering studies.

Many countries have published their own manuals or handbooks to guide field observations. The Swedish Traffic Conflict Technique, Dutch Traffic Conflict Technique, and German Traffic Conflict Technique, to name a few, have been successfully applied in many studies. It is worth noting that survey findings may vary depending on which technique is used, as the observational methods and definitions of conflict are different for each technique.

11.4 Field survey of traffic conflicts

The FHWA observer's manual presents the basic background information, definitions of typical traffic conflicts at intersections, and step-by-step instructions for persons who conduct traffic conflict field surveys (Parker Jr. and Zegeer, 1989). A survey usually involves several hours to several days of careful manual observation of traffic at a study location. It involves one or more observers performing a number of separate but related tasks to gather information regarding existing highway features, types of traffic control devices, conflict counts, volume counts, and crash data. The observer is required to judge the traffic problems, observe traffic, and record traffic events with the aid of datasheets, cameras, and/or video equipment.

Traffic conflicts generally are categorized by six primary types of conflicts: same direction, opposing left-turn, cross-traffic, right-turn-on-red, pedestrian, and secondary (Parker Jr. and Zegeer, 1989).

- Same-direction conflict occurs when the first vehicle slows and/or changes direction and places the following vehicle in danger of a rear-end collision. Four types of same-direction conflicts exist, based on the first vehicle's path: left-turn, same-direction; right-turn, same-direction; slow-vehicle, same-direction; and lane change conflict.
- Opposing left-turn conflict occurs when an oncoming vehicle makes a left turn, and places a second vehicle, going in the other direction, in danger of a head-on or broadside collision. Note that situations such as when a second vehicle is placed in danger of a collision because the driver of the second vehicle is running a red light are not treated as traffic conflicts under the general definition.
- Cross-traffic conflict occurs when a vehicle on the cross-street turns or crosses into the path of a second vehicle on the main street that has the right-of-way and places the second vehicle in danger of a rear-end, sideswipe, or broadside collision. There are six types of cross-traffic conflicts: right-turn, cross-traffic-from right; left-turn, cross-traffic-from-right; through, cross-traffic-from-right; right-turn, cross-traffic-from-left; left-turn, cross-traffic-from-left; and through, cross-traffic-from-left.
- Right-turn-on-red (RTOR) conflict occurs when an RTOR vehicle makes a turn and crosses into the lane of a second vehicle that has the right-of-way. There are two types of RTOR conflicts: opposing right-turn-on-red and right-turn-on-red-from-right.
- Pedestrian conflict occurs when a pedestrian walks in front of a vehicle that has the right-of-way and creates a possible collision situation. There are two types of pedestrian conflicts: pedestrian, far-side; and pedestrian, near-side conflict.
- Secondary conflict occurs when the second vehicle makes an evasive movement that places a third vehicle in danger of a collision. There are two types of secondary conflicts: slow-vehicle, same-direction secondary; and right-turn, cross-traffic-from-right secondary conflict.

Some representative intersection conflict situations are illustrated in Fig. 11.1.

This detailed classification is useful for pinpointing specific safety and operational problems in the field or in the office. After completing the fieldwork, the data should be assembled and analyzed to identify any treatable problems or special conflict situations. Please refer to the observer's manual (Parker Jr. and Zegeer, 1989) for specific procedures pertaining to materials and equipment preparation and onsite orientation to ensure uniform data collection.

11.5 Proximal surrogate safety measures

Despite its usefulness for observing traffic conflicts and diagnosing safety and operational issues, TCT is known for its varying quality control due to the experience and subjectivity of field observers. The approach has been challenged pragmatically, operationally, and conceptually during its 3 decades of practice. First, it is not possible to exhaust all evasive actions in the observer's manual, such as single vehicle and multivehicle (more than two) collisions. Overlooking such traffic conflict observations is detrimental to the sites with an overrepresentation of these conflicts. Second, whether or not an evasive action can be fully characterized by field observations is questionable because a crash is often the outcome of a chain of events. Third, many crashes happen without any evasive actions or with too many evasive actions (e.g., an overcautious driver reacts when there is no impending danger). These questions prompted the development of alternative methods.

On the other hand, proximal surrogate safety measures serve as a natural means of describing when "*two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged*" (Amundsen and Hyden, 1977). Once a collision course is established, appropriate time and/or distance measurements can quantify the probability of a collision. This section covers the definitions of conflict points, conflict lines, and representative proximal surrogate safety measures and includes examples of surrogate measures of safety on a roadway segment and at an intersection.

11.5.1 Collision course

A crash happens when vehicles coincide in the same place at the same time, whereas conflicts happen between vehicles that are on a collision course but do not collide due to evasive actions. The events can happen at a particular location (a conflict point) or during a range of times and locations (a conflict line) when vehicle paths cross or overlap (Hernandez, 1982). For instance, conflict points take place between through-moving and left-turning vehicles. Conflict lines can represent the range of

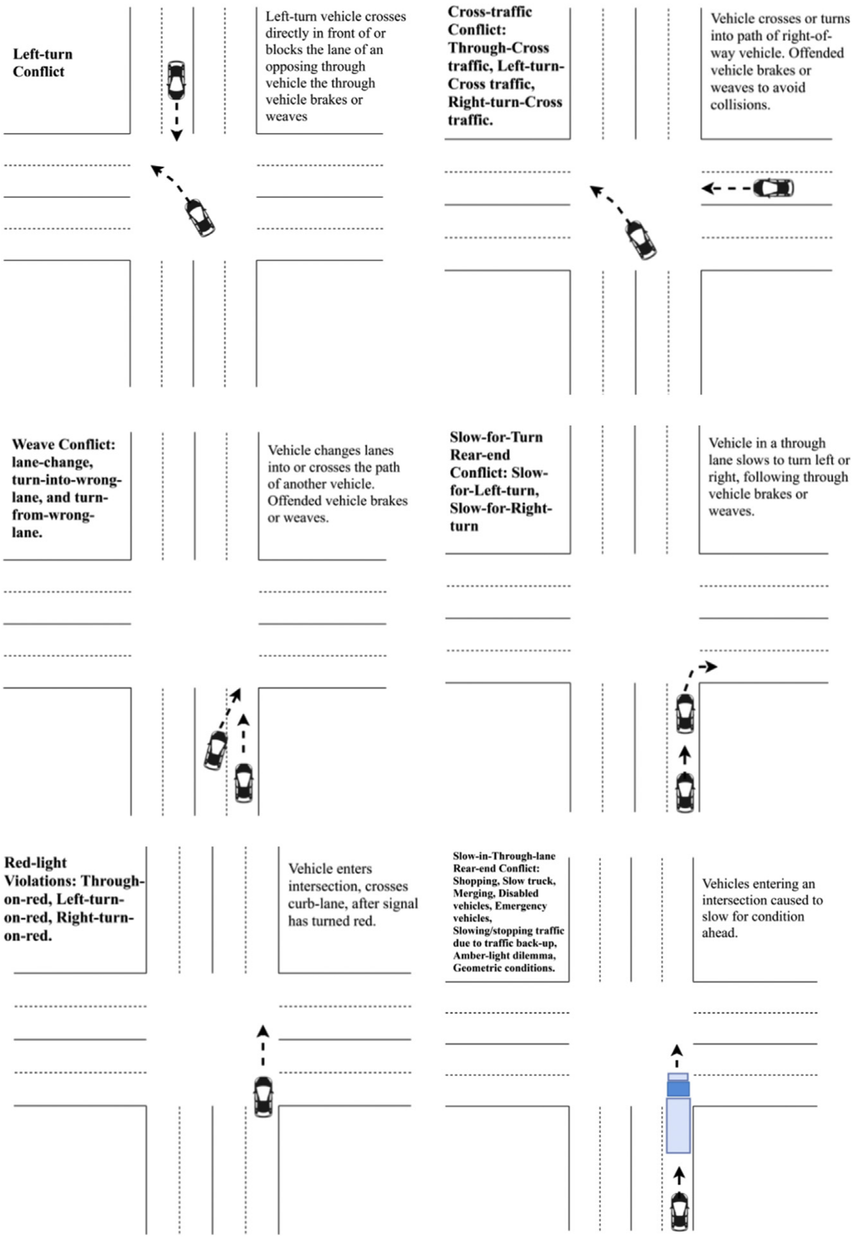


FIGURE 11.1 Representative intersection conflict situations. *Adapted from M.R. Parker Jr., C.V. Zegeer, Traffic Conflict Techniques for Safety and Operations: Observers Manual (No. FHWA-IP-88-027, NCP 3A9C0093), Federal Highway Administration, United States, 1989.*

conflicts caused by the merging movement of a right turn by the minor street traffic conflicting with the through traffic, and a left turn by the minor street traffic conflicting with the through traffic; the range of rear-end conflicts by the diverging movement of right-turn traffic and the range of lane-changing related conflicts when a vehicle suddenly changes lanes. Once the vehicle's path is determined, the conflicts due to crossing, merging, or diverging movements of traffic can be observed and measured. Collision course is an important concept for proximal surrogate measures as it establishes a definitive and fixed vehicle trajectory. A quantifiable indicator will then be established such as the time-based and distance-based proximal surrogate measures.

11.5.2 Time- and distance-based proximal surrogate safety measures

Temporal proximity-based measures are the most prominent surrogate measures because they integrate both the distance proximity and the vehicle speed. Other surrogate measures include distance-based proximity and deceleration rates.

11.5.2.1 Time to collision family

TTC or time measured to collision (TMTC), the most commonly used temporal proximity measure, was introduced by Hayward in 1971 (Hayward, 1971). It is defined as "*the time to collide if two vehicles continue at their present speed and along the same path*," and is expressed in Eq. (11.1).

$$TTC_i = \frac{D}{V_i - V_{i-1}} \tag{11.1}$$

where TTC_i denotes the TTC value of vehicle i, the subject vehicle, V_i denotes the speed of the subject (or the following) vehicle i, V_{i-1} denotes the speed of the front vehicle $i-1$, and D is the space between vehicles.

A variant is time to accident (TA) (more recently defined as crashes). It is the moment during which the evasive action takes place, defined as "*the time that remains to an accident from the moment that one of the road users starts an evasive action, if they had continued with unchanged speed and directions*."

TTC has several unique properties. First, TTC can be calculated only when the road users are on a collision course. Second, TTC is a continuous observation for a conflict line. Lastly, TTC cannot be directly observed, so it is calculated based on future motion prediction. A series of TTC values can be calculated along the conflict line, one for each time stamp. A low TTC value indicates a hazardous situation.

Time exposed time to collision (TET) and time integrated time to collision (TIT) are the two TTC indicators for a time period during which the calculated TTC is below a user-specified threshold value TTC^* (Minderhoud and Bovy, 2001). TET is the length of time a driver approaches the front vehicle with a TTC below a designated TTC threshold

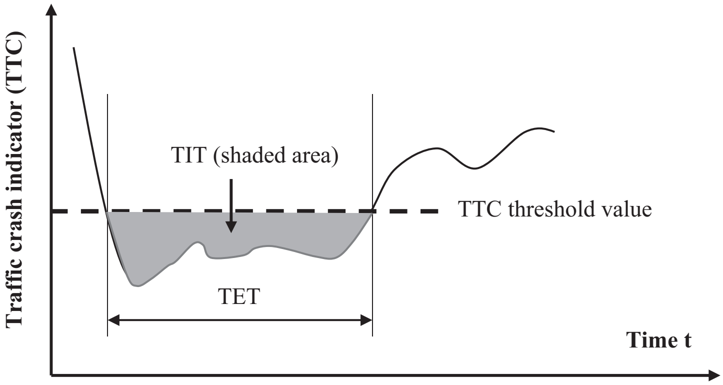


FIGURE 11.2 Concept of TIT and TET

(in Eq. 11.2) and TIT is the integral of the calculated TTC profile when it is below the threshold (in Eq. 11.3). Fig. 11.2 shows the conceptual presentation of TET and TIT.

$$TET = \sum_{t=0}^{T} \delta_i(t)\tau_{sc} \ \text{ and } \ \delta_i(t) = \begin{cases} 1 & \forall 0 \le TTC_i(t) \le \text{threshold value} \\ 0 & \text{otherwise} \end{cases} \tag{11.2}$$

$$TIT = \int_{t=0}^{T} [TTC^* - TTC_i(t)]dt \quad \forall 0 \le TTC_i(t) \le \text{threshold value} \tag{11.3}$$

where $TTC_i(t)$ is the TTC value of vehicle i at time t. $\delta_i(t)$ is an indicator variable whose value is set to be 1 if the $TTC_i(t)$ is between 0 and TTC threshold value; otherwise it is 0. The time frequency is calculated as $T = H/\tau_{sc}$ where H is the extended time period of study and τ_{sc} is the scan interval or time step (e.g., 0.1 s). The selection of TTC threshold value varies by study, by highway facility type, and by driver type. Mahmud et al. (2017) summarize the minimum and desirable TTC threshold values from the previous studies. For approaches at intersections, esp. signalized intersections, the minimum TTC threshold may be 1 s and the desirable value ranges from 1.5 to 3 s. For 2-lane rural roads, the desirable value may be 3 s. For nonsupported drivers, the desirable value may be 3.5 s as compared to supported drivers whose value may be 2.6 s. The interested reader is referred to Mahmud et al. (2017) for additional details.

TTC assumes that vehicles remain at a constant speed; this suggests that a collision happens only when the speed of the following vehicle is greater than that of the lead vehicle. This overly restrictive assumption ignores real-world driver behaviors. Modified time to collision (MTTC) was proposed to account for the difference in acceleration and the difference in speed between the lead and following vehicles (Ozbay et al., 2008; Laureshyn et al., 2010). In Eq. (11.4), MTTC is formulated for four different scenarios considering the relative distance, speed, and acceleration between the lead and following vehicles.

$$MTTC = \begin{cases} \max(t_1, t_2), & \text{if } \Delta a > 0 \\ \min(t_1, t_2), & \text{if } \Delta a < 0 \text{ and } \Delta V > 0 \\ t_3, & \text{if } \Delta a = 0 \text{ and } \Delta V > 0 \\ N/A, & \text{if } \Delta a \leq 0 \text{ and } \Delta V \leq 0 \end{cases} \tag{11.4}$$

where.
$t_1 = \frac{-\Delta V + \sqrt{\Delta V^2 + 2\Delta a D}}{\Delta a}$, $t_2 = \frac{-\Delta V - \sqrt{\Delta V^2 + 2\Delta a D}}{\Delta a}$, $t_3 = \frac{D}{\Delta V}$, $\Delta V = V_2 - V_1$, $\Delta a = a_2 - a_1$, $D = X_1 - X_2$. X_1, X_2, V_1, V_2, a_1, and a_2 are the position, speed, and deceleration rate of the lead and following vehicles, respectively. As can be seen, there are two possible outcomes of MTTC, t_1 and t_2. If both t_1 and t_2 are positive, the smaller is considered to be the MTTC vlaue; if one is positive and the other is negative, the positive one is considered to be the MTTC value. Also, TTC, t_3, is a special case of MTTC that happens when the relative acceleration rate equals zero.

Exercise 11.1

The following/response vehicle speed (V_2) and acceleration rate (a_2) are recorded every 1/10 s. The closest (front) vehicle for gap (D) and relative speed (ΔV) between the two vehicles are detected by the vehicle instrumented with sensors such as Mobileye. Calculate TTC and modified time to collision (MTTC) based on vehicle trajectory data.

Time (s)	D (m)	ΔV (m/s)	V_2 (m/s)	a_2 (m/s^2)
0	27	2.8958	19.3638	−0.0778
0.1	27	3.1806	19.3638	−0.0778
0.2	27	3.3889	19.3731	0.0823
0.3	26	3.4236	19.3731	0.0823
0.4	26	3.4653	19.1290	−0.2902
0.5	25	3.6736	19.1000	−0.2902
0.6	25	3.9792	19.0776	−0.3531
0.7	25	4.3194	19.0423	−0.3531
0.8	24	4.4306	19.0581	−0.2862
0.9	24	4.3125	19.0295	−0.2862

First, calculate the lead vehicle's velocity and acceleration rate. For instance, at "Time = 0.1"

Exercise 11.1 (*cont'd*)

$$V_1(0) = V_2(0) - \Delta V(0) = 19.3638 - 2.8958 = 16.4680 \ \ \text{m/s}$$

$$V_1(0.1) = V_2(0.1) - \Delta V(0.1) = 19.3638 - 3.1806 = 16.1832 \ \ \text{m/s}$$

$$a_1(0.1) = \frac{V_1(0.1) - V_1(0)}{0.1 - 0} = \frac{16.1832 - 16.4680}{0.1 - 0} = -2.8480 \ \ \text{m/s}^2$$

$$\Delta a = a_2(0.1) - a_1(0.1) = -0.0778 + 2.8480 = 2.7702$$

Next, according to Eq. (11.4), calculate t_1, t_2, and t_3.

$$t_1(0.1) = \frac{-\Delta V + \sqrt{\Delta V^2 + 2\Delta a D}}{\Delta a} = \frac{-3.1806 + \sqrt{3.1806^2 + 2 * 2.7702 * 27}}{2.7702} = 3.4142 \ \ \text{s}$$

$$t_2(0.1) = \frac{-\Delta V - \sqrt{\Delta V^2 + 2\Delta a D}}{\Delta a} = \frac{-3.1806 - \sqrt{3.1806^2 + 2 * 2.7702 * 27}}{2.7702} = -5.7111 \ \ \text{s}$$

$$t_3(0.1) = \frac{D}{\Delta V} = \frac{27}{3.1806} = 8.4890 \ \ \text{s}$$

Finally, determine TTC and MTTC.

$$TTC = t_3(0.1) = 8.4890 \ \ \text{s};$$

$$MTTC = \max(t_1, t_2) = \max(3.4142 - 5.7111) = 3.4142 \ \ \text{s};$$

The final output is listed below[a]

	Derived value				Output			SSM	
Time (s)	**V_1 (m/s)**	**a_1 (m/s^2)**	**ΔV (m/s)**	**Δa (m/s^2)**	**t_1 (s)**	**t_2 (s)**	**t_3 (s)**	**TTC (s)**	**MTTC(s)**
0	16.4680		−2.8958						
0.1	16.1833	−2.8472	−3.1806	2.7694	3.4142	−5.7111	8.4891	8.4891	3.4142
0.2	15.9842	−1.9908	−3.3889	2.0732	3.7244	−6.9937	7.9672	7.9672	3.7244
0.3	15.9495	−0.3472	−3.4236	0.4296	5.6158	−21.5554	7.5943	7.5943	5.6158
0.4	15.6637	−2.8577	−3.4653	2.5674	3.3487	−6.0481	7.5030	7.5030	3.3487
0.5	15.4264	−2.3735	−3.6736	2.0833	3.4433	−6.9701	6.8053	6.8053	3.4433
0.6	15.0984	−3.2793	−3.9792	2.9262	2.9917	−5.7114	6.2827	6.2827	2.9917
0.7	14.7229	−3.7558	−4.3194	3.4027	2.7686	−5.3074	5.7878	5.7878	2.7686
0.8	14.6275	−0.9533	−4.4306	0.6672	4.1317	−17.4136	5.4169	5.4169	4.1317
0.9	14.7170	0.8944	−4.3125	−1.1806	N/A	N/A	5.5652	5.5652	N/A

[a] *The difference in values between the example and table is caused by rounding errors.*

continued

Exercise 11.1 (*cont'd*)

TTC displays a decreasing trend but overall, it is more than the desirable threshold value ranging from 1.5 to 3 s. MTTC, however, falls into the desirable threshold value range in a few moments. In addition, when $\Delta a \leq 0$ and $\Delta V \leq 0$, MTTC value is not applicable.

11.5.2.2 Encroachment time family

All relevant indicators in encroachment time family involve the encroachment action. Encroachment-related indicators can be effectively illustrated through a time-space diagram. Fig. 11.3 shows a typical left-turn conflict in which the opposite through driver perceives a potential collision when a left-turning vehicle comes into his/her path at location P1 during time T1. The driver takes an evasive action by reducing speed, therefore avoiding a collision by arriving at the conflict location P3 during time T4. The left-turn vehicle would have arrived at the conflict location P3 at time T2 had the through driver not reduced speed. Likewise, the through vehicle would have arrived P3 at time T3 had the speed not been reduced. So, the through vehicle would have missed the collision by a narrow margin of (T3−T2).

The PET, the most well-known indicator in this family, is defined as the length of time from the end of encroachment to the time that the vehicle who possesses the right-of-way arrives at the potential point of collision (T4−T2). Thus, PET measures a situation in which a collision is avoided with only a small margin or a near miss. TTC requires a collision course,

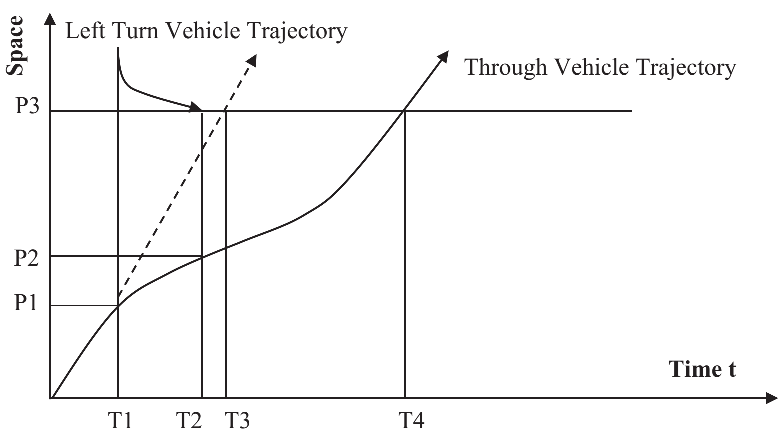


FIGURE 11.3 Demonstration of PET. *Adapted from B.L. Allen, B.T. Shin, P.J. Cooper, Analysis of traffic conflicts and collisions, Transp. Res. Rec. J. Transp. Res. Board (667) (1978) 67−74.*

whereas PET needs only the time difference of two observed moments to represent the temporal proximity of road users.

One variant of PET is gap time, or the time between the end of encroachment and the expected arrival at the potential point of collision, provided that the vehicle maintains the original approach speed and direction (T3−T2).

The second variant is encroachment time (ET), the time during which the infringement takes place (T2−T1).

The third variant is time advantage (TAdv), which is defined as the time difference between two vehicles continuing at their present speed and path to the point of conflict. TAdv is like the TTC version of PET because it offers continuous observations of the interactions between road-users over time and space (Laureshyn et al., 2010).

11.5.2.3 Proportion of stopping distance

Proportion of stopping distance (PSD) is a spatial proximity indicator that is defined as the ratio between the current distance to the potential point of collision and the minimally acceptable stopping distance, as expressed in Eq. (11.6) (Allen et al., 1978).

$$PSD = \frac{RD}{V^2/2d} \tag{11.5}$$

where *PSD* is the proportion of stopping distance, *RD* is the remaining distance to the potential collision point, *V* is the approaching velocity, and *d* is the acceptable maximum deceleration rate.

11.5.2.4 Other indicators

The common evasive action taken by a driver to avoid a collision is reducing speed. Experts have suggested several deceleration-based measures, including the deceleration rate and the maximum observed deceleration rate of the vehicle during a conflict (Gettman and Head, 2003); however, these measures are based on observations of the actual braking of a driver and they will not work unless the driver reacts to the hazard. The maximum available deceleration rate (MADR) and the deceleration rate to avoid collision (DRAC) have been proposed as alternatives. MADR could be unique to each vehicle under prevailing traffic and environmental circumstances, as it considers pavement conditions and variations in vehicle braking capacity. A conflict may be initiated due to a speed change of the lead vehicle such as slowing down or stopping, and the following vehicle may react by reducing its speed. Thus, DRAC is defined as the differential speed (ΔV) between a following vehicle and its front vehicle ($V_2 - V_1$) divided by their gap time calculated as $\frac{(X_1 - X_2) - L_1}{V_2 - V_1}$. The DRAC is expressed as Eq. (11.5) (Almqvist et al., 1991):

$$DRAC = \frac{(V_2 - V_1)^2}{(X_1 - X_2) - L_1} = \frac{\Delta V^2}{D} \tag{11.6}$$

where V_1, X_1, and L_1 are the speed, position, and vehicle length for the front vehicle, V_2, X_2 are the speed and position for the following vehicle; and other variables are noted previously. DRAC is updated every time step, commensurate with a uniform maximum comfortable deceleration rate such as 3.35 m/s^2 or 11.2 ft/s^2.

However, none of the abovementioned indicators explicitly measures the possible outcome of a potential collision. The variables associated with injury severity include the type of road users involved, speed, mass, type of collision, and collision angle. Among these variables, the vehicle speed is the direct input to measure the severity or the impact of a collision. A representative indicator, Delta-V (Eq. 11.7), is an object's change in velocity due to an impact with another object in physics. A large change in the magnitude of velocity over a short period of time suggests extensive forces, resulting in serious injuries.

$$\Delta V = |V_e - V_i| \tag{11.7}$$

where ΔV is the magnitude of the change in velocity, V_e is the end velocity, and V_i is the initial velocity.

Exercise 11.2

Using the same data in Exercise 11.2, calculate DRAC based on vehicle trajectory data.

According to Eq. (11.6), the gap between the front and following vehicles $D = (X_1 - X_2) - L_1$ and the output of DRAC is listed below.

Time (s)	D (m)	ΔV (m/s)	DRAC (m/s^2)
0	27	2.8958	
0.1	27	3.1806	0.3747
0.2	27	3.3889	0.4254
0.3	26	3.4236	0.4508
0.4	26	3.4653	0.4619
0.5	25	3.6736	0.5398
0.6	25	3.9792	0.6334
0.7	25	4.3194	0.7463
0.8	24	4.4306	0.8179
0.9	24	4.3125	0.7749

Exercise 11.2 (*cont'd*)

As none of the calculated DRAC exceeds the maximum comfortable deceleration rate, which is set to be 3.35 m/s^2, the collision risk between the two vehicles is low.

Table 11.1 summarizes the key elements for major surrogate safety indicators, which include their definitions, strengths, and limitations and suitability for collision type (Sohel Mahmud et al., 2017).

11.6 Theoretical development of safety surrogate measures

When Hydén's (1987) validated the Swedish Conflicts Technique, he compared the processes before injury accidents to those preceding conflicts, which led him to propose the "Safety Pyramid." The pyramid involves a hypothetical continuum that describes road—user interactions at different events, from less severe situations to fatal crashes, for which clearly defined boundaries may not exist (see Fig. 11.4). The severity outcome of traffic events, however, is visible: unsafety acts, near misses, minor accidents, and serious accidents, even death. The base of the pyramid symbolizes unsafe acts that are more frequently observed, and the top of the pyramid represents the most severe and most rare events such as fatal or injury crashes. If this continuum is an accurate representation of the relationship between serious conflicts and crashes, the frequency of the very severe but rare crashes can be predicted based on the known frequency of the less severe but more common events.

Proximal surrogate measures represent a family of continuous variables that can be used to register conflicts under predetermined thresholds. However, inconsistent validation results between threshold-based conflicts and observed crashes have led to a lack of consensus on which threshold values should be utilized. Therefore, research has shifted away from data-driven methods that involve the development of empirical conflict—crash ratios or the determination of threshold values through statistical goodness-of-fit to theory-based approaches. Extreme value models (EVM) based on the extreme value theory (EVT) have led the way regarding rationalizing the continuous transition from conflicts to crashes through observable traffic events. Tracing back to seminal work from Fisher and Tippett (1928) titled "*Limiting Forms of the Frequency Distribution of the Largest or Smallest Members of a Sample*," EVT is a well-developed statistical theory that studies the extreme realizations of a given

TABLE 11.1 Comparison of major surrogate safety indicators.

Indicator	Definition	Limitations	Advantages	Suitability for collision type
Time to collision (TTC)	The time until a collision between the vehicles would occur if they continued on their present course at their present rates.	Assume consecutive vehicles will keep constant speeds; ignore many potential conflicts due to acceleration or deceleration discrepancies; can provide the magnitude of crashes but not their severity; collision course must exist, TTC index cannot be estimated in a finite number where the leading vehicle is faster than following.	TTC is far more frequently used in practice than PET or TA due to theoretical issues; TTC was more informative than PET; many automobile collision avoidance systems or driver assistance systems have used TTC as an important warning criterion; applicable for work zone safety analysis, applicable in postprocessor such as SSAM	Rear-end, turning/weaving, hit objects/parked vehicle, crossing and hit pedestrian.
Time exposed time to collision (TET)	Summation of all moments (over the considered time period) that a driver approaches a front vehicle with a TTC-value below the threshold value	Does not provide the various severity levels of different TTC values below the threshold value; if TTC value is lower than the threshold, does not affect the TET indicator value; highly data-intensive and attainable only in a simulation environment.	Can be calculated separately for per user class, can be applied in the comparison of a do-nothing case with an adapted situation; suited for application in microscopic simulation studies of traffic; easy to include small TTC value due to including of time-dependent TTC values of all subjects.	Same as TTC

Time integrated time to collision (TIT)	Integral of the TTC profile during the time it is below the threshold	Difficult to interpret its meaning for complexity to determine; not preferable to use in comparative studies in which simulation tools are applied to generate trajectories; benefits are small due to the uncertainties in driver behavior.	Level of safety of collision can be derived; can be applied in the comparison of a do-nothing case with an adapted situation; suitable for microscopic simulation studies of traffic; easy to include small TTC value due to including of time-dependent TTC values of all subjects.	Same as TTC
Modified time to collision (MTTC)	Modified models that considered all of the potential longitudinal conflict scenarios due to acceleration or deceleration discrepancies.	Obtaining the field speed of both users and the distance gap in an evolution process is difficult and has to rely on other approaches; not fit for lane changing or head-on collision; does not reflect the severity of the collision	More advance than TTC; consider driving discrepancies.	Vehicle−vehicle crash same as TTC
Time to accident (TA)	Time to accident (TA) is the time that remains to an accident from the moment that one of the road users starts an evasive action if they had continued with unchanged speed and directions	Often criticized for relying heavily on the subjective judgment of speed and distance. Mainly rely on the evasive action. Other same as TTC	Widely used; easy to measure; can be done by both manually or by video analysis, couple of manuals have been developed in different countries.	Same as TTC

Continued

TABLE 11.1 Comparison of major surrogate safety indicators.—cont'd

Indicator	Definition	Limitations	Advantages	Suitability for collision type
Post encroachment time (PET)	The time between the moment that a road user (vehicle) leaves the area of potential collision and the other road user arrives collision area.	Only useful in the case of transversal (i.e., crossing) trajectories (right angle collision); cannot reflect changes with the dynamics of safety-critical events over a larger area; levels of severity, as well as impact of a conflict, are not taken into account;	PET is more appropriate than TTC for intersecting conflicts; PET can be easily extracted; PETs can be easily estimated using photometric analysis in video or simulated environment; PET represents the driver behaviors.	Mainly for right angle or crossing crash, hit pedestrian. Merging/diverging, head on (to a certain extent).
Proportion of stopping distance (PSD)	Ratio between the remaining distance to the potential point of collision and the minimum acceptable stopping distance.	Based on evasive actions; PSD provides a higher percentage of vehicle interaction and time exposure to conflict than TTC and DRAC, hence less focus on specific safety problems.	Single vehicle conflict with fixed or unfixed objects can be evaluated; easy for observation and calculation.	Hit object (on-road or roadside), overturning
Deceleration rate to avoid the crash (DRAC)	Differential speed between a following/response vehicle and its corresponding subject/lead vehicle (SV) divided by their gap time.	Fail to accurately identify the potential traffic conflict situation; not suitable for lateral movement.	Explicitly considers the role of differential speeds and decelerations in traffic flow.	Rear-end, hit object/parked vehicle, hit pedestrian, merging and diverging maneuvers.
Crash potential index (CPI)	Probability that a vehicle DRAC exceeds its maximum available deceleration rate (MADR)	Not suitable for lateral movement; mainly applicable at the intersection	Address some of the issues found in DRAC like vehicle braking capability for prevailing road and traffic conditions.	Turning accident, right angle

Modified from S.M.S. Mahmud, L. Ferreira, S. Hoque, A. Tavassoli, Application of proximal surrogate indicators for safety evaluation: a review of recent developments and research needs, IATSS Res. 41 (2017) 153–163.

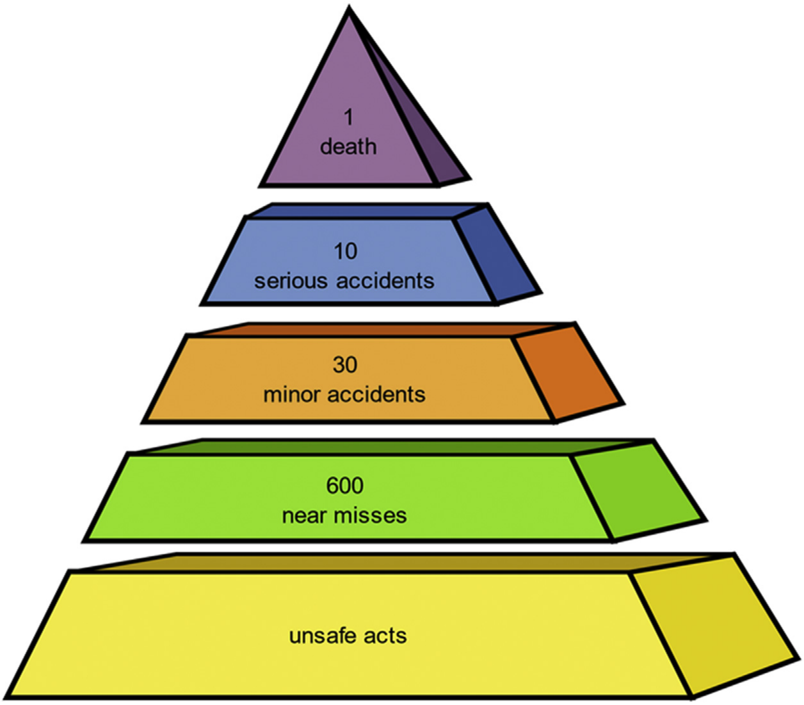


FIGURE 11.4 Safety risk pyramid.

distribution function. Extreme value distributions can help define the limiting distributions of sample maxima.[1] EVT has been used to quantify the stochastic behavior of a process at extremely large or small levels and the process needs to be continuous so it can be extrapolated for unobserved levels. Aligning with the objective to use more frequent traffic conflicts to predict less frequent crashes, EVT's application in highway safety can be formulated as follows:

$$F(C) = F(H)R(C|H) \tag{11.8}$$

where $F(C)$ is the frequency of crashes for the road entity, $F(H)$ is the frequency of observed traffic conflicts for the road entity, and $R(C|H)$ is the risk of crash estimated with the fitted extreme value distributions given the conflict H of the road entity.

EVMs have been used extensively in the fields of hydrology, meteorology, and finance to forecast the probability of extreme weather events, earthquakes, flooding, and financial crises. Songchitruksa and Tarko (2006)

[1] The normal distribution is a limiting distribution (asymptotic distribution) for sample averages, according to the central limit theorem (CLT).

introduced the generalized extreme value (GEV) model to the field of safety surrogate measures and estimated the frequency of right-angle crashes at urban intersections based on measured PET. Later, Tarko (2012) applied the generalized Pareto (GP) distribution to predict road departure crashes with near road departure events. Compared to traffic conflict techniques, the EVM has three noticeable advantages: (1) the crash proximity measure precisely defines the surrogate event; (2) the EVM does not require an arbitrary ratio converting the surrogate event frequency into the crash frequency; and, (3) the crash risk, given the surrogate event, is estimated for any condition based on the observed crash proximity.

The remainder of this section introduces two families of EV distributions that have different approaches for sampling extreme events: (1) the block maxima or minima (BM) using the GEV; and (2) the peak over threshold (POT) using the GP. Both approaches have been used to model the distributional properties of the proximity between road users observed at time or in space and estimate the probability of collision conditional upon the observations.

11.6.1 Block maxima using the generalized extreme value distribution

Observations in BM are first grouped by certain lengths of time or distance and then extreme values are extracted from each block, as illustrated in Fig. 11.5. These extreme values are assumed to follow the GEV distribution.

Let $\{X_1, X_2, \ldots, X_n\}$ be a set of independently and identically distributed random observations and $M_n = \max\{X_1, X_2, \ldots, X_n\}$ be a block maximum of n values. If the normalized variable $M_n^* = (M_n - b_n)/a_n$ converges, then

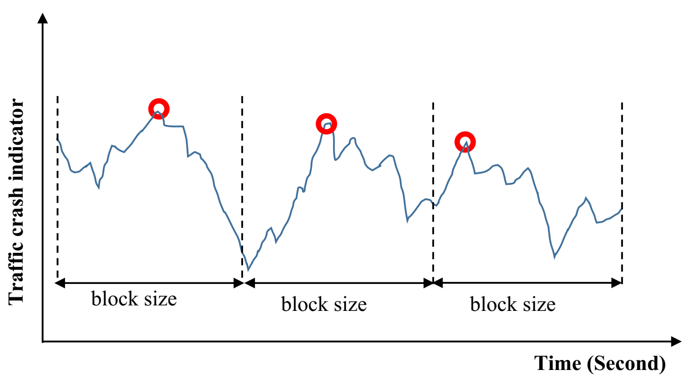


FIGURE 11.5 Extreme value model: block maxima (BM).

M_n will converge to a GEV distribution, and $G(z) = P_r\{(M_n - b_n)/a_n \leq z\}$. The standard GEV function is expressed by

$$G(m) = \begin{cases} \exp\left(-\left[1+\xi\left(\frac{m-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right) \xi \neq 0 \\ \exp\left(-\exp\left(-\frac{m-\mu}{\sigma}\right)\right) \xi = 0 \end{cases} \tag{11.9}$$

where μ is the location parameter, σ is the scale parameter, and ξ is the shape parameter. If ξ is positive, then GEV becomes the Frechet cumulative distribution function (CDF) with a finite lower bound of $\frac{\mu-\sigma}{\xi}$; if ξ is negative, then GEV becomes the (reversed) Weibull CDF with finite upper bound $\frac{\mu+\sigma}{|\xi|}$; if ξ is zero, then GEV is the Gumbel CDF.

In the BM method, it is important to find the appropriate size of the block so that it is large enough to include truly extreme values from enough observations and in the meantime, is small enough to have a sample size greater than 30. Note that the sample size is the block count if only one extreme value is chosen from each block. Sometimes, the r-largest statistics, where r is greater than one, are utilized to include more than one extreme value from each block. The form of block size can vary by study: either be fixed like the PET that is observed in a 15-min block (e.g., Songchitruksa and Tarko, 2006) or a variable like the TTC that is observed during each passing maneuver (e.g., Farah and Azevedo, 2017).

11.6.2 Peak over threshold using the GP distribution

Exceedance statistics describe the statistical properties of a random variable that exceeds a threshold value. A common application is to use the POT data in flood estimation. In the context of surrogate safety measures, we can assume S to be a continuous variable that quantifies the risk of a collision (also called as the severity of conflict) between two road users. The higher the S value, the higher the collision risk. The probability density distribution of S at a signalized intersection is shown in Fig. 11.6 where S_2 is the threshold value beyond which a risky event is registered, and S_3 is the threshold value for collisions (Svensson, 1998).

The exceedance statistics consider an observation to be extreme if it exceeds a predetermined threshold value. Let $\{X_1, X_2, \ldots, X_n\}$ be a set of independently and identically distributed random observations. The distribution function of exceedance X over a threshold μ is

$$F_\mu(x) = \Pr(X - \mu \leq x | X > \mu) \tag{11.10}$$

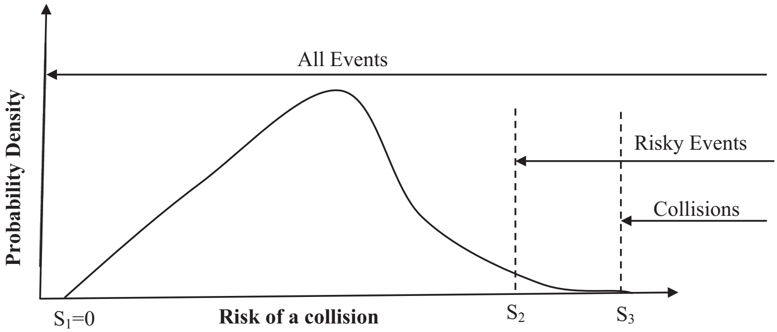


FIGURE 11.6 Risk of collision at signalized intersections. *Adapted from Å. Svensson, A Method for Analyzing the Traffic Process in a Safety Perspective (PhD dissertation), Bulletin 166, University of Lund, Lund, Sweden, 1998.*

When the threshold μ is high, $F_\mu(x)$ can be approximated by the standard cumulative distribution function of the GP distribution, defined by

$$G(x) = \begin{cases} 1 - \left[1 + \left(\dfrac{\xi(x-\mu)}{\sigma}\right)\right]^{-\frac{1}{\xi}} & \xi \neq 0 \\ 1 - \exp\left(-\dfrac{(x-\mu)}{\sigma}\right) & \xi = 0 \end{cases} \tag{11.11}$$

where ξ is the shape parameter, σ is the scale parameter, and $x-\mu$ is an exceedance in the range $0 \leq x - \mu < \infty$, if $\xi \geq 0$; or, $\mu \leq x < \mu - \frac{\sigma}{\xi}$, if $\xi < 0$. If ξ is zero, then the GP distribution applies to tails that decrease exponentially, such as the exponential distribution; if ξ is positive, then the GP distribution applies to tails that decrease as a polynomial, such as Student's t (heavy tail); if ξ is negative, then the GP distribution applies to finite tails such as the beta distribution (light tail).

Similar to the block size in the BM approach that determines the sample size, the threshold value in the POT approach determines the sample size as well. An optimal threshold should be chosen to balance the need for selecting extreme values as well as the sufficient sample size. A high threshold produces fewer observations that may have a large variance; a low threshold may treat observations with ordinary values as extremes and compromise the asymptotic distribution of extreme values. The typical approaches to determining an optimal threshold value are the "mean residual life plot" and the "assessment of parameters stability" (Coles, 2001).

Ideally, the EVM is applied to a specific conflict point or to a conflict line at a specific location (e.g., intersection or segment). The sample size may not be adequate when the observation time is relatively short. A common approach to fix this issue is to pool data from other conflict points/lines or from other locations to increase the sample size. However, this approach leads to the issue of nonstationarity, which is that the parameters in the EV distribution may not be the same. A viable solution to address the nonstationarity issue is to allow the parameters of the EV distribution to vary. Songchitruksa and Tarko (2006) and Zhang et al. 2014a,b defined the location parameter μ in GEV as a function of traffic volume, $\mu = \boldsymbol{x}'\boldsymbol{\beta}$, where is a set of covariates that characterize the changes in μ, and β is the vector of regression coefficients.

The issue of serial dependency or serial correlation happens when extreme observations are correlated with their prior values because they are drawn sequentially. This may be more problematic to the BM method than to the POT method because extreme values are drawn sequentially from the blocks. In the case of a lane change event, the observed PETs may be dependent on prior lane change maneuvers. The standard method of detecting serial dependency is to plot observations chronologically or order them over space. Serially correlated observations will reveal a trend over time, with peaks and valleys that typically repeat themselves over fixed intervals. Since the mid-1990s, several methods for declustering a series of extremes to extract a set of independent extremes have been discussed. An additional method for handling clustered extremes is the deletion of neighboring observations on both sides of a local maxima.

11.6.3 Block maxima or peak over threshold

Zhang et al. 2014a,b conducted a study of freeway lane change maneuver crashes to compare the BM and POT approaches when modeling PET. The authors found that when the observation time period is relatively short, the POT approach is superior to the BM approach regarding data utilization, estimate accuracy, and estimation reliability. The sample size is equal to the observation time period divided by the block size; therefore, when the observation time is short, the block interval also needs to be short to ensure an adequate sample size. The short interval reduces the number of observations within each block and arbitrarily elevates some ordinary observations to be extremes. Hence, models estimated from a mixture of extreme and ordinary observations may be biased and ineffective. On the other hand, the POT approach makes full use of possible extremes provided that a threshold is properly set up. In their study, the observation time for most of the freeway segments is approximately 3 h, and the interval is 5-min, resulting in a block size that ranges from 21 to 41.

Another way to compare the model performance is through the shape parameter. According to Smith (1985), the maximum likelihood estimators are not likely to be attainable if the shape parameter $\xi < -1.0$; whereas, the estimator possesses the usual asymptotic properties and thus more reliable (note: the theory of asymptotic and limit laws are essential to formulate the distributions of extremes) if $\xi > -0.5$. In Zhang's study, two out of 29 freeway segments yielded a shape parameter that was greater than −0.5 in the BM approach, whereas the POT produced eight.

Model parameters can be estimated with the maximum likelihood estimation method in R package "exTremes" or "evd: Functions for Extreme Value Distributions." Details on the statistical properties of the GEV and GP distributions can be found in Coles (Coles, 2001).

Safety literature regarding EVT has reported considerably different performance outcomes between the BM and POT approaches. The statistical community continues to discuss the merits and circumstances of both approaches. Readers are encouraged to refer to (Zhang et al., 2014a,b; Tarko, 2012; Farah, 2017) for more technical details and to run their own comparative studies based on the data and study design.

Example 11.1

A driving simulator experiment was set up to estimate the probability of head-on collisions during passing maneuvers (Farah et al., 2017). *The driving scene was projected onto a screen in front of the driver and the image was updated at a rate of 30 frames per second. The subject vehicle is overtaking a front vehicle when another vehicle is approaching fro the opposite direction. The simulator experiment produced 1287 completed passing maneuvers, including nine collisions. The minimum TTC is measured at the end of the passing maneuver. Use the BM and POT approach to estimate the probability of a head-on collision and its confidence interval.*

First, in the BM approach, a GEV distribution is fitted using the non-crash passing maneuvers and the respective minimum TTC measurements. The block intervals are defined as the entire passing maneuvers. Fig. 11.7 (left) shows the CDF of the minimum TTC for the full dataset, and Fig. 11.7 (right) shows the CDF of the minimum TTC for the filtered data (a minimum TTC less than or equal to 1.5 s).

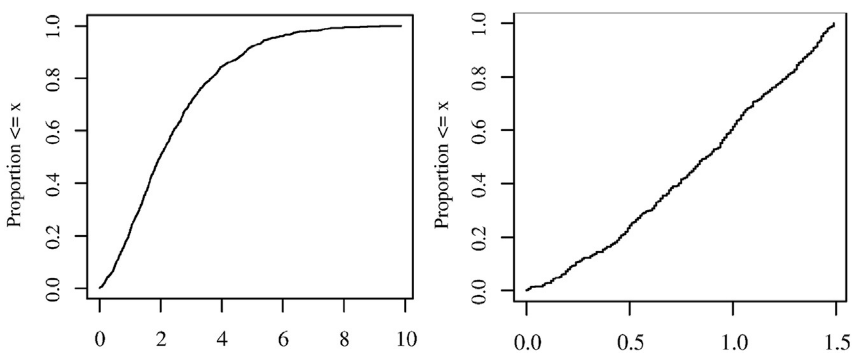
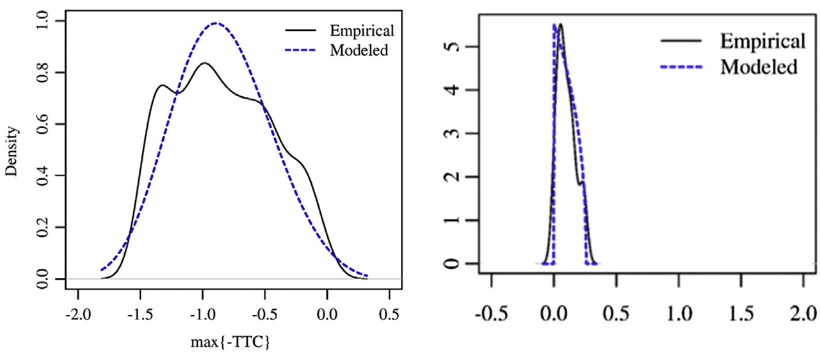


FIGURE 11.7 CDF of the minimum TTC. *From H. Farah, C. Lima Azevedo, Safety analysis of passing maneuvers using extreme value theory, IATSS Res. 41 (2017) 12–21.*

Example 11.1 (*cont'd*)

A smaller TTC value means a higher risk for head-on collision. For the sake of the maxima model, the negative TTC value is used because a higher negative TTC value indicates a higher risk for head-on collision. In the stationary block maxima model for the maxima of the negated values of TTC (i.e., maximum $(-TTC)$), the probability of head-on collision should be $(-TTC) \geq 0$. The driving simulator experiment used a 1.5 s filter and recorded 463 near head-on collisions and nine actual collisions. Then, the probability of a head-on collision given the presence of a near head-on collision event during passing is: $\frac{9}{463+9} = 0.0191$ with a 95% confidence interval (0.0088, 0.0359).

Finally, the fitted distribution has the following parameters for a GEV CDF: $\mu = -0.993\ (0.012), \sigma = 0.383\ (0.0163), \xi = -0.236\ (0.05)$ where the values in parenthesis are the standard errors. Fig. 11.8 presents the kernel density functions of the empirical and modeled negated TTC. According to the stationary model for the $(-TTC)$, the estimated probability of a head-on collision given the observed passing maneuver is 0.0179 with a 95% confidence interval of (0.0177, 0.0182) (Fig. 11.8, left).



GEV; block maxima (BM)
$\mu = -0.993\ (0.012)$,
$\sigma = 0.383\ (0.0163)$,
$\xi = -0.236\ (0.05)$

GPD; Peak Over Threshold (POT)
$\mu = 0$,
$\sigma = 0.181\ (0.0393)$,
$\xi = -0.703\ (0.1930)$
Threshold value is -0.25 s

FIGURE 11.8 Kernel density plot for the BM and POT model (Farah et al., 2017).

In the POT approach, the optimal threshold value can be calculated through statistical methods such as mean residual life and stability plots (Coles, 2001). Different stationary models were fitted using four different threshold values of -1.5, -1.0, -0.5, and -0.25 for $(-TTC)$,

continued

Example 11.1 (*cont'd*)

respectively. Among the values, the estimated probability of a head-on collision that is closest to the empirical data is 0.00628 with a 95% confidence interval of (0.00612, 0.00643) yielded with the -0.25 s threshold (Fig. 11.8, right).

Nonstationary models have been tested in the POT method by including several covariates (e.g., speed, passing rate, curvature) in the scale parameter formulation (σ). Nonstationary models have also been tested in the BM method in the location parameter formulation (μ). All tests and validations lead to the conclusion that the BM approach yields more stable results compared to POT. The predicted probability of head-on collisions based on the BM approach was very close to the probability of head-on collisions based on the empirical data.

11.7 Safety surrogate measures from traffic microsimulation models

Traffic microsimulation models, which replicate driver and vehicle behavior, have been used extensively to mimic the process of vehicle movement and interactions in a traffic stream. The performance, accuracy, and reliability of contemporary traffic microsimulation models have been significantly improved through the calibration of parameters related to driver behavior such as car following, lane changing, and gap acceptance. The use of microscopic traffic simulation models drastically increases the efficiency and reduces the cost of collecting surrogate measures. However, the obvious shortcoming of microsimulation models is that they are incapable of "producing" collisions. This limitation casts doubt on whether surrogate measures taken from simulated traffic events can be a reliable predictor of crash frequency. Nevertheless, the simulation models are ideal tools for comparing highway design and traffic operational alternatives before their implementation.

As each vehicle can be traced in a computer simulation through its trajectory, its location, speed, and acceleration or deceleration are recorded on a second-by-second basis. The detailed and timestamped vehicle positions allow researchers to measure and estimate the spatial and temporal proximity between vehicles. The FHWA sponsored the development of the Surrogate Safety Assessment Model (SSAM) from traffic simulation packages (https://highways.dot.gov/safety/ssam/surrogate-safety-assessment-model-overview) (Gettman et al., 2008; Pu et al., 2008). SSAM is a software application developed to automatically identify, classify, and evaluate traffic conflicts in the vehicle trajectory data output from microscopic traffic simulation models. The model was built on the outputs of existing traffic simulation models such as PTV Vissim[2], and has built-in statistical analysis features for conflict frequency and severity measures that can aid analysts in the design of safe traffic facilities. The SSAM approach has been assessed by comparing different surrogate safety measures. It has been validated through field studies that compared its output to real-world crash records (Fan et al., 2013; Huang et al., 2013).

It should be noted that over the last few years, microsimulation, despite the limitation described earlier, has been used to estimate the safety effects of connected and autonomous vehicles (CAVs). As the deployment of CAVs is very limited, there are not enough crash data to properly evaluate their safety performance. The simulation, in this context, can be used to examine different penetration rates (say 10%–100%) and how CAVs interact (i.e., traffic conflicts) with human-driven vehicles (Jeong et al., 2017; Mousavi et al., 2019, 2020). Input variables, such as headways and reaction times, need to be adjusted for properly simulating CAVs on (usually urban) transportation networks. The latest version of Vissim (2020) has a module that can be used specifically for CAVs.

11.8 Safety surrogate measures from video and emerging data sources

Measuring the spatial and temporal proximity between vehicles requires vehicles to be traced and their trajectory information to be extracted. As discussed in Chapter 2—*Fundamentals and Data Collection*, on-site video cameras can be used for recording the vehicle trajectory, while the computer vision technique allows tracking moving objects and detecting traffic conflicts from videos. Microsoft Corp., the City of Bellevue, WA and University of Washington (UW) jointly developed a software application that utilizes a city's existing traffic cameras to count near-miss collisions and classify vehicles by turning movement (through, left or right), direction of approach (northbound, southbound, eastbound, westbound), and mode (car, bus, truck, motorcycle, bicycle, and pedestrian). Additionally, speed and acceleration rate can be calculated continuously from the vehicle trajectory to better understand the driver's steering and braking behaviors (Loewenherz et al., 2017). The

[2] PTV Vissim is a microscopic multimodal traffic flow simulation software package developed by PTV AG in Karlsruhe, Germany.

video analytics technologies will play a more important role in active safety management as video surveillance becomes more prevalent.

Vehicle trajectory information can also be gathered from in-vehicle longitudinal data, or GPS. Naturalistic driving study (NDS) data (Guo et al., 2010; Wu and Jovanis, 2012) and connected vehicle data (Liu and Khattak, 2016; He et al., 2018) are two emerging data sources that provide a great opportunity for gaining a better understanding of collision mechanisms and developing novel safety metrics. SHRP 2 Naturalistic Driving Study (SHRP 2 NDS) is the largest coordinated safety program ever undertaken in the United States. The SHRP 2 program consists of an NDS data and a companion Roadway Information Database, RID. The NDS data were collected from more than 3500 volunteer passenger-vehicle drivers aged 16−98 during a 3-year period, with most drivers participating for one to 2 years (2010−12). Additional details about the program background and the database of detailed data can be found at https://insight.shrp2nds.us/.

The Safety Pilot Model Deployment (SPMD) program, a comprehensive data collection effort that took place under real-world conditions in Ann Arbor, Michigan, covered over 73 lane-miles and included approximately 3000 pieces of onboard vehicle equipment and 30 pieces of roadside equipment. In the SPMD program, basic safety messages (BSMs) communicated between connected vehicles transmit approximately 10× per second in-vehicle data (e.g., vehicle size, position, speed, heading, acceleration, brake system status) can be an important supplement to a traditional crash data-oriented safety analysis. SPMD data are text-based, accompanied by a downloadable data dictionary and metadata document and are available for use via the research data exchange (www.its-rde.net).

Traffic conflicts have become the most prominent and promising proactive safety measures for identifying safety concerns and evaluating the effectiveness of safety treatments in the absence of crash data. Researchers have put significant efforts into developing techniques and metrics that properly record traffic conflicts. This section has discussed both evasive action-based and proximity-based surrogate measures. As emerging data sources such as the BSM from V2V and V2I technologies and modern video image processing technologies become more available and pervasive, large-scale, continuous, and automatic traffic conflict observations will become more readily available. Rich data sources will accelerate the advances of surrogate safety measures by including new and more complex crash types and by extending and calibrating the extreme value models.

References

AASHTO, 2010. Highway Safety Manual, 1st Edition ed. American Association of State Highway and Transportation Officials, Washington, D.C.
Allen, B.L., Shin, B.T., Cooper, P.J., 1978. Analysis of traffic conflicts and collisions. Transp. Res. Rec. J. Trans. Res. Board (667), 67–74.
Almqvist, S., Hyden, C., Risser, R., 1991. Use of Speed Limiters in Cars for Increased Safety and a Better Environment. Transportation Research Record 1318, Transportation Research Board, Washington, DC, pp. 34–39.
Amundsen, F., Hyden, C., 1977. Proceedings of the 1st Workshop on Traffic Conflicts. Norway, Oslo.
Chin, H.-C., Quek, S.-T., 1997. Measurement of traffic conflicts. Saf. Sci. 26 (3), 169–185.
Coles, S., 2001. An Introduction to Statistical Modeling of Extreme Values. Springer-Verlag, London, UK.
Fan, R., Yu, H., Liu, P., Wang, W., 2013. Using VISSIM simulation model and Surrogate Safety Assessment Model for estimating field measured traffic conflicts at freeway merge areas. IET Intell. Transp. Syst. 7 (1), 68–77.
Farah, H., Lima Azevedo, C., 2017. Safety analysis of passing maneuvers using extreme value theory. IATSS Res. 41, 12–21.
Fisher, R.A., Tippett, L.H.C., 1928, April. Limiting forms of the frequency distribution of the largest or smallest member of a sample. In: Mathematical Proceedings of the Cambridge Philosophical Society (Vol. 24, No. 2, pp. 180–190). Cambridge University Press.
Gettman, D., Head, L., 2003. Surrogate safety measures from traffic simulation models. Transp. Res. Rec. 1840 (1), 104–115.
Gettman, D., Pu, L., Sayed, T., Shelby, S., Siemens, I.T.S., 2008. Surrogate Safety Assessment Model and Validation (No. FHWA-HRT-08-051). United States. Federal Highway Administration. Office of Safety Research and Development.
Glauz, W.D., Migletz, D.J., 1980. Report 219: Application of Traffic Conflict Analysis at Intersections. TRB, National Research Council, Washington, D.C.
Guo, F., Klauer, S.G., Hankey, J.M., Dingus, T.A., 2010. Near crashes as crash surrogate for naturalistic driving studies. Transp. Res. Rec. 2147 (1), 66–74.
Hayward, J.C., 1971. Near Misses as a Measure of Safety at Urban Intersection. The Pennsylvania State University.
He, Z.X., Qin, X., Liu, P., Sayed, M.A., 2018. Assessing Surrogate Safety Measures Using a Safety Pilot Method Deployment (SPMD) Dataset, Transportation Research Record. https://doi.org/10.1177/0361198118790861.
Hernandez, V., 1982. A Microscopic Digital Computer Simulation of Traffic Conflicts at 4-way Fixed Time Signalized Urban Intersections. Ph.D. Dissertation. University of California, Los Angeles.
Huang, F., Liu, P., Yu, H., Wang, W., 2013. Identifying if VISSIM simulation model and SSAM provide reasonable estimates for field measured traffic conflicts at signalized intersections. Accid. Anal. Prev. 50, 1014–1024.
Hydén, C., 1987. The Development of a Method for Traffic Safety Evaluation: The Swedish Traffic Conflicts Technique. Lund Institute of Technology, Lund.
Ismail, K., Sayed, T., Saunier, N., 2011. Methodologies for aggregating indicators of traffic conflict. Transp. Res. Rec. 2237, 10–19.
Jeong, E., Oh, C., Lee, S., 2017. Is vehicle automation enough to prevent crashes? Role of traffic operations in automated driving environments for traffic safety. Accid. Anal. Prev. 115–124.
Johnsson, C., Laureshyn, A., De Ceunynck, T., 2018. In search of surrogate safety indicators for vulnerable road users: a review of surrogate safety indicators. Transp. Rev. 38 (6), 765–785. https://doi.org/10.1080/01441647.2018.1442888.

Laureshyn, A., Svensson, Å., Hydén, C., 2010. Evaluation of traffic safety, based on micro-level behavioural data: theoretical framework and first implementation. Accid. Anal. Prev. 42, 1637–1646. https://doi.org/10.1016/j.aap.2010.03.021.

Liu, J., Khattak, A.J., 2016. Delivering improved alerts, warnings, and control assistance using basic safety messages transmitted between connected vehicles. Transp. Res. C Emerg. Technol. 68, 83–100.

Loewenherz, F., Bahl, V., Wang, Y., March 2017. Video analytics towards vision zero. ITE J. 25–28.

Mahmud, S.M.S., Ferreira, L., Hoque, S., Tavassoli, A., 2017. Application of proximal surrogate indicators for safety evaluation: a review of recent developments and research needs. IATSS Res. 41, 153–163.

Minderhoud, M.M., Bovy, P.H., 2001. Extended time-to-collision measures for road traffic safety assessment. Accid. Anal. Prev. 33, 89–97. https://doi.org/10.1016/S0001-4575(00)00019-1. PMID:11189125.

Mousavi, S.M., Osman, O.A., Lord, D., 2019. Impact of urban arterial traffic LOS on the vehicle density of different lanes of the arterial in proximity of an unsignalized intersection for autonomous vehicle vs. conventional vehicle environments. In: International Conference on Transportation and Development, Alexandria, VA.

Mousavi, S.M., Lord, D., Mousavi, S.R., Shirinzad, M., 2020. Safety performance of autonomous vehicles on an urban arterial in proximity of a driveway. In: Paper Presented at the 99th Annual Meeting of the Transportation Research Board, Washington, D.C.

Ozbay, K., Yang, H., Bartin, B., Mudigonda, S., 2008. Derivation and validation of new simulation-based surrogate safety measure. Transp. Res. Rec. J. Transp. Res. Board 2083, 105–113. https://doi.org/10.3141/2083-12.

Parker Jr., M.R., Zegeer, C.V., 1989. Traffic Conflict Techniques for Safety and Operations: Observers Manual (No. FHWA-IP-88-027, NCP 3A9C0093). Federal Highway Administration, United States.

Perkins, S.R., Harris, J.I., December 7, 1967. Traffic Conflict Characteristics; Accident Potential at Intersections. General Motors Research Publication GMR-718.

Proceedings of the 1st Workshop on Traffic Conflicts, 1977. Oslo, Norway.

Pu, L., Joshi, R., Energyd, S., 2008. Surrogate Safety Assessment Model (SSAM)–software User Manual (No. FHWA-HRT-08-050). Turner-Fairbank Highway Research Center.

Saunier, N., Sayed, T., 2008. Probabilistic Framework for Automated Analysis of Exposure to Road Collisions. Transportation Research Record, 2083, pp. 96–104.

Smith, R.L., 1985. Maximum likelihood estimation in a class of nom-regular cases. Biometrika 72, 67–90.

Songchitruksa, P., Tarko, A.P., 2006. The extreme value theory approach to safety estimation. Accid. Anal. Prev. 28, 811–822.

Svensson, Å., 1998. A method for analysing the traffic process in a safety perspective. Department of Traffic Planning and Engineering, Lund Institute of Technology, Lund, Sweden, p. 174.

Tarko, A.P., 2012. Use of crash surrogates and exceedance statistics to estimate road safety. Accid. Anal. Prev. 45, 230–240 doi:10.1016/j.aap. 2011.07.008.

Wu, K.F., Jovanis, P.P., 2012. Crashes and crash-surrogate events: exploratory modeling with naturalistic driving data. Accid. Anal. Prev. 45, 507–516.

Zheng, L., Sayed, T., 2019. From univariate to bivariate extreme value models: approaches to integrate traffic conflict indicators for crash estimation. Transp. Res. C Emerg. Technol. 103, 211–225.

Zheng, L., Ismail, K., Meng, X., 2014. Traffic conflict techniques for road safety analysis: open questions and some insights. Can. J. Civ. Eng. 41 (7), 633–641.

Zheng, L., Ismail, K., Meng, X.H., 2014. Freeway safety estimation using extreme value theory approaches: a comparative study. Accid. Anal. Prev. 62, 32–41.