CHAPTER 17

SURROGATE MEASURES OF SAFETY

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ABSTRACT

Purpose – This chapter overviews surrogate measures of safety to help better understand the related challenges and opportunities. The chapter is meant to serve as a primer for practitioners looking for alternative methods of evaluating safety where crashes are lacking or are insufficient.

Approach – The historical perspective and the current state-of-the-art thinking are presented in an organised manner with a focus on fundamental concepts, traffic measurement techniques and estimation of the relationships between surrogate events and collisions.

Findings – An analysis of the published research and its findings indicates that traffic conflicts are the most promising surrogates. They enable evaluation of the safety implications of a wide range of road and traffic conditions. The required ecological consistency between conflicts and collisions can be ensured by sufficient nearness of conflicts to collisions. Several methods of estimating the relationship between conflicts and crashes are discussed. Behavioural measures of safety are also discussed. Although easier to measure than conflicts, behavioural measures should be used with caution.
Research on surrogate measures of safety may provide a basis for improving microsimulation models as tools of safety evaluation.

Practical implications – Current changes in vehicle and road instrumentation affect safety at a rate that exceeds the efficiency of the traditional crash-based methods of safety analysis. Accurate and quick measurement of safety with surrogate measures offers a viable solution. They are also a necessary condition of gaining a better understanding of safety and finding more effective solutions for safety problems.

Keywords: Traffic conflicts; crash surrogates; risky events

INTRODUCTION

This chapter is the final of six chapters that collectively represent state of the practice methodologies for both understanding and predicting the safety performance of transport networks. This chapter describes methods for using surrogate measures of crashes to examine risk and is a complement to the appropriate management of cross-sectional crash data (Chapter 12), the management of crash data observed at the same transport network locations over time (Chapter 13), a focus on crash data that contain a relatively large number of zeros (numerous sites recording no crashes in a particular time period) (Chapter 14), methods for examining and understanding crash severity (Chapter 15) and methods for identifying high-risk sites or blackspots on a transport network (Chapter 16).

Previous chapters have presented specific research methods and the knowledge gained by applying these methods to crash data. While the value of crash data is undisputable, there is also a considerable amount of concern about the downsides of crash data, such as the low quality of the data, the difficulty in tracking the sequence of events leading to a crash and, consequently, the limitations of crash data for both acquiring new knowledge and evaluating new safety improvement methods.

One of the problems with crash data is the focus on crash events while neglecting successful events that do not lead to crashes. Crash-focused data are particularly useful in exploring the risk of injury and fatality given a crash, but they do not support research exploring the risk of a crash itself particularly well where risk is defined in both cases as the probability that exposure to a hazard (crash or being on a road) leads to a negative consequence (Ropeik, 2002). Current safety studies compensate for missing information about the
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events between crashes with roughly assessed or highly aggregate quantities, such as the overall exposure and the average risk, during considerably long periods of months or years. The fallacy of this approach, which is a necessity rather than a choice, was discussed by Davis (2004).

Data highly aggregated with limited or non-existent representation of causality cannot support timely and accurate estimation of safety. The need for a quick and accurate estimation of safety has been amplified with the growing presence of modern technology on roads and in vehicles that quickly change road safety in a way not always sufficiently controlled or even understood. Traditional crash-based methods of acquiring safety knowledge cannot keep up with these changes. There is an upside to this situation however. Modern technologies may help collect safety-related data at and between crashes that may be utilised to provide a never-before available insight to the risk of a crash and the risk of a severe outcome if a crash occurs. The crash risk is used in its probabilistic meaning when applied to short periods. Alternatively, the high risk of crashes can be detected for certain conditions or locations by analysing the frequency and severity of crashes over longer periods by using representative periods.

The earliest mentioning of alternative methods of viewing and analysing safety that do not rely solely on crash data can be found in Perkins and Harris (1968). Thus, the exploration of alternative measures of safety, called surrogate measures of safety to emphasise the need to replace or supplement crash data, has been carried for at least 50 years. This has resulted in various concepts and a variety of definitions, sometimes inconsistent with each other. It is impossible to present all of them, their chronology and impact in a way that would acknowledge all who contributed to the area, especially when only a single chapter is devoted to this topic and not an entire book. Because of that, this chapter focusses on surrogate events and related concepts that are internally consistent and have a good chance, in the judgement of the author, to be useful in the emerging area of autonomous vehicles and computer microsimulation for safety analysis. To make the reader aware that surrogate events are not the only type of surrogate measures, behaviour-related surrogate measures are briefly covered. In summary, the primary objective of this chapter is to introduce surrogate measures of safety as being viable and of growing importance, while the ambition of giving credit to all the documented efforts is not pursued.

Considerable research efforts in the 1970s and 1980s established fundamentals of traffic conflicts but they did not deliver a practical method of measuring safety. The recently observed revival of this research area is motivated by the growing need for timely safety measurement and the new
opportunities afforded by modern technologies. Furthermore, the improved statistical methods have raised hope again for applying the traffic conflicts technique to deliver quick measurements and gain a better understanding of safety. At least three benefits of traffic conflicts and other surrogate measures of safety are widely understood:

1. Detecting the excessive risk of crashes on the road.
2. Improving the knowledge of conditions leading to a crash or increasing the crash probability.

Finding a way to achieve these benefits will lead to effective crash avoidance systems in modern vehicles, well-estimated safety relationships and efficient methods for evaluating safety improvements.

As already mentioned, this chapter focuses on the leading surrogate measures of safety in the mainstream research that could become the basis for practical methods and tools of safety analysis. Although the driver perspective is presented in the discussion as vital and difficult to ignore, this chapter is intended for transportation engineers and therefore traffic flow is the dominant perspective of the discussion; surrogate measures of safety are presented as potential tools for evaluating road and traffic control improvements.

A brief discussion of surrogate events follows this introduction and identifies traffic conflicts as the most promising surrogates of crashes. Then, the historical context and recent proposals related to traffic conflicts are presented, as well as the challenges of observing traffic conflicts in naturalistic driving and roadside studies. Correct representation and estimation of the relationship between conflicts and crashes are critical, and the various current models and the prospect of their estimation are discussed. To close the chapter, the frequently proposed or used surrogate measures and computer simulation are also discussed in separate sections, followed by a chapter summary.

**HISTORICAL PERSPECTIVE OF TRAFFIC CONFLICTS**

The concept of a dangerous interaction is defined in De Silva (1942). Although the term ‘traffic conflict’ was used for dangerous interactions by Klebelsberg (1964), its first application to identifying safety-related problems is attributed to the Detroit General Motors Laboratory (Perkins & Harris, 1968). At that time, the meaning was somewhat wider than today and included not only interactions between vehicles but also traffic violations
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(Campbell & King, 1970; Perkins & Harris, 1968). For example, entering an intersection on a red signal was a traffic conflict even when no actual interaction between vehicles took place. Hayward (1971) narrowed the meaning of traffic conflicts to dangerous interactions where at least one of the involved drivers had to change speed or direction to avoid collision. He estimated the times to collision (TTC) repeatedly updated during observed conflicts. At each calculation instant, the current distance between vehicles was divided by the current speed difference. The vehicles’ positions were recorded on a 16-mm film and the TTC calculated with a computer program. He considered an event a conflict if the TTC was shorter than 1 s.

Since the late 1970s, many authors in the United States and Europe have contributed to developing the traffic conflicts technique, including producing standards and national methods (Chin & Quek, 1997; Hauer, 1978; Hayward, 1971; Hydén, 1987; Sayed & Zein, 1999; Shinar, 1984; Svensson, 1998; van der Horst, 1982, 1990; van der Horst & Kraay, 1986; van der Parker & Zegeer, 1989; Zegeer & Deen, 1977). The first Workshop on Conflict Techniques in Oslo in 1977 brought a formal definition of traffic conflicts: ‘A traffic conflict is an observable situation in which 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’. This definition was further modified in the Dutch method, DOCTOR (van der Horst & Kraay, 1986), by adding a condition for a ‘recordable’ crash warranted with a considerable probability of personal injury or material damage.

Several authors have tried to connect traffic conflicts with crashes with mixed results (Hauer & Garder, 1986; Migletz, Glauz, & Bauer, 1985; Williams, 1981). Another line of research attempted to improve the technique by revisiting the measurement of the conflict’s nearness to a collision (Hayward, 1971; Hydén, 1987; Minderhoud & Bovy, 2001; Svensson & Hydén, 2006; van der Horst, 1990; Vogel, 2003). The past work on measuring traffic conflicts to reduce or eliminate human observers and estimating conflict–collision relationships is discussed in separate sections later in this chapter. A comprehensive overview of the work on traffic conflicts and other surrogate measures can be found in Zheng, Ismail and Meng (2014c).

Campbell, Joksch and Green (1996) introduced the concept of precipitating events, such as driver error, that trigger a sequence of events potentially leading to a crash. This idea was later used by Davis, Hourdos, Xiong, and Chatterjee (2011) in a more formalised manner. Tarko (2012) considered inclusion of near-crash events without evasive manoeuvres among surrogate events. These events are not acceptable and are most likely caused by road users’ errors. Furthermore, certain causes of crashes (or precipitating events), such
as a driver having a heart attack or a vehicle’s mechanical failure, offer little chance to apply evasive manoeuvres, thus the corresponding traffic conflicts with observable evasions may be quite infrequent.

AETIOLOGY OF TRAFFIC CONFLICTS AND CRASHES

Many surrogate measures of safety have been proposed and used in road and traffic engineering. It is widely accepted that a good surrogate measure of safety must meet three conditions:

1. It properly captures the effect of road and traffic changes.
2. It is correlated with the crashes affected by these changes.
3. It is practical.

Properly defined traffic conflicts meet all three of the following conditions: (1) traffic conflicts are affected by traffic, road and other factors; (2) although a conflict is not a crash, a chain of events connects the two events that constitutes the crash causality and, furthermore, traffic conflict and crash occurrences share many traffic and road factors; and (3) traffic conflicts happen more frequently than crashes and current measurement techniques allow their observation with a reasonable level of accuracy.

Fig. 1 postulates two general sources of aetiological consistency between good surrogates and crashes: association and causality. A causal relationship between a crash and its surrogate is denoted by the arrows. Surrogate events and crashes are correlated through common conditions they share (B Conditions in Fig. 1). A specific surrogate event or measure is useful for studying the safety effect of a certain treatment only if the treatment applies to (changes) B Conditions that affect both the surrogate and the crashes. Thus, a surrogate that shares many conditions also supports the evaluation of many treatments.

Surrogate events, to be adequate, must be related to crashes through a common cause. For instance, confusing road design may cause both driver error (precipitation event) and a consequent situation that requires an evasion to correct the error. At this critical moment the situation may turn into a conflict or a crash. From this perspective, a conflict and a crash belong to the same class of risky events brought about by the same cause. Thus, a traffic conflict and a crash tend to be similar by manner of interaction (right-angle, rear-end, roadway departure), type of road users involved (vehicles, trucks, pedestrians) and other event attributes.
A Conditions affect the frequency of surrogate events but do not affect the frequency of crashes. If a traffic conflict is incorrectly defined by allowing TTC to be too long, some intentional events acceptable by drivers will be misclassified as undesirable conflicts. For example, an efficient training of drivers may increase drivers’ confidence and their acceptance of shorter TTC without increasing the frequency of crashes.

On the other hand, increased frequency of steering failures in vehicles (C Conditions) does not have to lead to an increased frequency of observable conflicts if most of the steering failures end up as crashes. A more interesting case is a slippery pavement downstream of the spot where drivers start braking in response to a hazard. If the traffic conflict is defined through a TTC measured at the beginning of the evasive manoeuvre (Hydén, 1987), then the frequency of detected traffic conflicts will remain unchanged while the frequency of crashes will increase due to unsuccessful evasive manoeuvres. Applying the minimum TTC, on the other hand, would detect the change in the minimum value, helping to detect the increased frequency of conflicts.

The aetiological consistency of conflicts and collisions promotes a wide range of B Conditions and a narrow range of A and C Conditions (Fig. 1). The aetiological consistency requires that conflicts and crashes belong to the same class of risky events. Thus, the manner of conflict (e.g., right-angle conflict) is consistent with the manner of crash (right-angle crash between the same traffic movements as in a conflict). Furthermore, a traffic conflict must be the result of a driver error as most crashes are. To claim that the observed
conflict is the result of an error the conflict must be a traffic interaction that is not acceptable to the involved drivers. The closeness of a collision and the quickness of the evasive manoeuvre are often the only available evidence to decide that the interaction is a conflict if the drivers are not interviewed.

The quickness of a driver’s response to a traffic event has been used as a sole criterion to detect a traffic conflict in naturalistic driving, where it is easier to observe the behaviour of a subject vehicle than its interaction with other vehicles (Bagdadi, 2013; Dozza & González, 2012; Wu & Jovanis, 2013). This attempt generated a large number of false positives, because drivers’ responses were inadequate for the traffic situation or difficult to interpret. Drivers were responding rapidly to the close proximity of other vehicles around them even if they were moving along non-conflicting trajectories. Such behaviour indicates that a close proximity of another vehicle is not desirable and it is the effect of a driver’s error. In fact, a rapid and not fully controlled response to an error in close proximity of another vehicle may lead to a collision even if the original trajectories were not conflicting. On the other hand, right-angle collisions recorded by Japanese police at an intersection in Tokyo included a large number of cases without any attempts from drivers to avoid the crash (Ueyama, 1997). The lack of awareness of the hazard is the explanation. Thus, cases of ‘near-misses’ without evasive manoeuvres are the result of human errors (Tarko, 2012). In other words, a close proximity between road users in traffic is the manifestation of an operational failure, particularly if a potential collision may lead to a severe outcome.

It can be concluded from this discussion that properly defined traffic conflicts or near-crashes have the potential to serve as comprehensive surrogate measures of safety that would be useful in a wide range of road, traffic, human conditions and treatment studies. This statement is particularly true for studies addressing the risk and rate of crashes in order to prevent crashes from occurring. Use of traffic conflicts to study the severity of crashes may be much more challenging than studying the crash risk or frequency.

MEASURES OF CRASH PROXIMITY

The closeness (or proximity) to a collision can be measured in time via TTC or post-encroachment time (PET). It can also be measured in space as the distance between two road users or between a road user and an obstruction. The selection of a measure of proximity affects the traffic conflict’s ability to reflect certain safety factors and to be applicable to certain types of risky events.
Hayward (1971) calculated the TTC at a sequence of instants by dividing the distance between two vehicles on \((x,y)\) plane at a certain instant with the instantaneous speed difference (Fig. 2). It was assumed that the speeds and the directions of travel observed at the instant remain unchanged. Hayward recommended the minimum TTC reached during the interaction as a measure of crash proximity. Hydén (1987), on the other hand, proposed the proximity to crash to be measured with the time to accident (TTA) calculated at the moment when the evasive action is initiated. This measure requires detecting the beginning of the evasive manoeuvre, which may not always be obvious, and it does not reflect the effectiveness of the evasive manoeuvre on the crash proximity. TTC and TTA are not applicable to risky events without evasive manoeuvres.

PET involves two elements: (1) the conflict area and (2) the order in which two vehicles pass the conflict area. PET for a right-angle conflict is measured between the time when the first vehicle leaves the conflict area and the time when the second vehicle enters the conflict area (Fig. 3). In the car-following case, PET is equivalent to a time headway and it requires that the second vehicle moves faster than the first. PET cannot be applied to collisions with stopped vehicles or fixed obstructions. On the other hand, it does apply to risky events without evasive manoeuvres.

Hayward proposed the TTC calculation for a general case of two vehicles based on the speed difference in the \((x,y)\) plane (Fig. 2). The differential speed \(\Delta V\) must point out at the other vehicle to ensure existence of the TTC value. Otherwise, the two vehicles miss each other in the hypothetical collision area.
and PET can be calculated instead. Calculation of PET in such a general case is even more complex than TTC. PET applies to near-crashes without evasive manoeuvres, but it is not applicable to near-crashes with fixed obstructions.

Vehicles’ paths and speeds are important for proper interpretation of the collision closeness and the severity of potential collision. In other words, the speeds of vehicles during a surrogate event must be sufficiently high to constitute a dangerous outcome of the potential collision and to indicate that the event resulted from human error. Some studies combine the proximity with the speeds of the vehicles to arrive at measures that combine the closeness to the potential collision and the severity of the outcome of the potential crash (Hydén, 1987; van der Horst & Kraay, 1986). The following section discusses surrogate events with a focus on crash proximity, taking the assumption that the speeds of the interacting vehicles warrant a sufficiently serious hazard. This and other measures of proximity are discussed in Gettman, Pu, Sayed and Shelby (2008) and Laureshyn, Svensson and Hydén (2010).

**OBSERVING TRAFFIC CONFLICTS**

Observing how traffic progresses from normal situations to high-risk interactions between vehicles can reveal events and their circumstances that direct traffic development towards or away from a collision. Such observations under similar conditions for a sufficiently long period may help identify the key factors of the pre-collision process and evaluate the risk of a crash.

An inherent problem with observing traffic to analyse safety was noted by Hydén (1987). Observing severe traffic conflicts (close to a crash, almost crash) ensures aetiological consistency between the observed events and the corresponding collisions, but this benefit comes at the cost of a dramatically increased observation time. Songchitruxsa and Tarko (2006) concluded that observing surrogate events to estimate the frequency of crashes at an intersection with extreme value statistics may require several weeks. This data
collection period is much longer than the 1 or 2 days recommended by existing traffic conflict techniques that offer already estimated conflict–collision relationships based on previous studies at many similar intersections and crash data collected over several years. The downside of the existing traffic conflict techniques is their lack of applicability to new road designs or after considerable changes in overall road safety.

Research on traffic observation techniques for studying safety focusses on two general types of observations: in-vehicle and roadside. The in-vehicle method (naturalistic driving) is centred on individual drivers and their behaviours, and interactions with other drivers along the route. Sufficiently complete and accurate measurements are possible if the vehicle is properly instrumented. Even then, the most reliable observations are of the participating drivers inside instrumented vehicles, but measuring their interactions with the road and other vehicles is much more challenging (Hallmark et al., 2011; Hunt, Vandervalk, & Snyder, 2011). For that reason, some authors have investigated the possibility of detecting traffic conflicts solely based on a driver’s behaviour (Dozza & González, 2012; Wu & Jovanis, 2013). The results indicate that the physical proximity of interacting vehicles, whether in time or space, is important for correctly interpreting driver behaviour.

The early roadside observation techniques resorted to manual recording of traffic conflict observations (Sayed & Zein, 1999; van der Horst & Kraay, 1986; Zegeer & Deen, 1977). The subjective classification of traffic interactions as conflicts was inaccurate and inconsistent (Grayson, Hydén, Kraay, Muhlrad, & Oppe, 1984; Shinar, 1984). To reduce subjectivity, Hayward (1971) introduced the TTC measured by an observer equipped with a monitor and 18-mm film. A similar technique but with a more advanced video technology was used by Hydén (1987), and video-based TTC measurements have advanced significantly since then. The most advanced methods today reduce the role of human observers but do not eliminate them completely (Saunier & Sayed, 2008; Saunier, Sayed, & Ismail, 2010; Sayed, Ismail, Zaki, & Autey, 2012; Sayed, Zaki, & Autey, 2013). In some studies the traditional definition of traffic conflict with extrapolated speeds along known paths was expanded to the spatial distributions of the paths (Saunier & Sayed, 2008).

Only severe interactions leave no doubt of human error, making these interactions aetiological consistently with crashes. This premise led to observing rare events requiring a long observation time as already mentioned. Any technique that requires human supervision seems impractical. Fortunately, there are new generations of sensors, including LiDAR and light field cameras, which promise better accuracy and easier automation of measurements.
Roadside observations utilise sensors positioned at optimal locations. These sensors allow tracking multiple vehicles and vulnerable vehicles with similar accuracy but only within the range determined by the position and capabilities of the roadside sensors. Another limitation is the lack of personal information about observed objects. Thus, many important variables are unavailable or difficult to observe (e.g., driver’s age, driving experience, personality traits and current psychological states, as well as the technical conditions of the pavement and vehicle).

The naturalistic driving and roadside observation techniques have intrinsic weaknesses that are difficult to overcome. Integrating the two types of observations collected at multiple sources might be the answer.

THE CONFLICT–COLLISION RELATIONSHIP

Many research efforts have been focussed on conforming and estimating the relationship between traffic conflicts and crashes. The SHRP2 program deployed more than 2,000 vehicles for almost 1 year to collect safety data. Fewer than 200 crashes (Hauer & Garder, 1986; Migletz et al., 1985; Williams, 1981) were observed during that period. It is clear that collisions must be supplemented with conflicts or other relevant surrogates to gain better insight into the safety conditions. One important question is the relationship between conflicts and collisions. The progress in estimating the relationship between collisions and conflicts is shown in Table 1. The models are listed in the order they are discussed here, which does not follow the order of their publication.

The Type 1A model in Table 1 was proposed by Hauer (1982) and later estimated by Migletz et al. (1985) and Hydén (1987) based on an observed number of collisions and conflicts at multiple locations. The focus was on the coefficient $K$, which was assumed to be fixed. The data themselves were the most difficult challenge. Collisions are so infrequent that it takes dedicated agencies a long period of time to record a sufficient number of these events; it is believed that a considerable number still remain unreported. The details of a traffic event leading to a crash are typically poorly documented. On the other hand, traffic conflicts are expensive and troublesome to observe, thus only much shorter observation periods are practical. Consequently, crash period $T$ is much longer than conflict period $t$ and conditions $Y$ of crashes are different from conditions $X$ of conflicts. The strong heterogeneity of these conditions – mostly aggregated or unknown for crashes – combined with the typically small samples might be the main cause of, at best, mixed results of the first attempts to estimate the conflict–collision relationship. Another
problem is that the coefficient $K$ should be assumed dependent on conditions $(Y, X)$. The Type 1B model, proposed by Hauer and Garder (1986), is an extension of the early version by considering the conflict severity $s$.

The Type 2 model assumes that the relationship between the collisions and conflicts may be different for different conditions. It was estimated with count models, and the conflict rates are included among the explanatory variables (El-Basyouny & Sayed, 2013; Guo et al., 2010; Sayed & Zein, 1999). Conditions $X$ and $Y$ may still be inconsistent.

### Table 1. Models of Conflict–Collision Relationship.

<table>
<thead>
<tr>
<th>Type</th>
<th>Model Form</th>
<th>References</th>
</tr>
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<tbody>
<tr>
<td>Type 1A</td>
<td>$\text{Accidents}(T,Y) = K(\text{Conflicts}(t,X))$</td>
<td>Hauer (1982)</td>
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<td></td>
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<td>Migletz et al. (1985)</td>
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<td></td>
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<td>Hydén (1987)</td>
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<tr>
<td>Type 1B</td>
<td>$\text{Accidents}(T,Y) = \sum K_s \cdot \text{Conflicts}(t,X)$</td>
<td>Hauer &amp; Garder (1986)</td>
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<td></td>
<td></td>
<td>Sayed &amp; Zein (1999)$^a$</td>
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<td></td>
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<td>Guo, Lauer, Hankey &amp; Dingus (2010)</td>
</tr>
<tr>
<td>Type 2</td>
<td>$\text{Accidents}(T,Y) = K(Y,X) \cdot \text{Conflicts}(t,X)$</td>
<td>Wu &amp; Jovanis (2012)$^b$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>El-Basyouny &amp; Sayed (2013)</td>
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<tr>
<td>Type 3</td>
<td>$\text{Accidents}(t,X) = \sum R_s(X) \text{Conflicts}(t,X)$</td>
<td>Davis et al. (2011)</td>
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<tr>
<td></td>
<td></td>
<td>Campbell et al. (1996)</td>
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<td>Tarko &amp; Songchitruksa (2005)</td>
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<td></td>
<td>Songchitruksa &amp; Tarko (2006)</td>
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<tr>
<td>Type 4</td>
<td>$\text{Accidents}(t,X) = R(X) \cdot \text{Conflicts}(t,X)$</td>
<td>Tarko (2012)</td>
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<td></td>
<td></td>
<td>Jonasson &amp; Rootzén (2014),</td>
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<td></td>
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<td>Zheng, Ismail &amp; Meng (2014a)</td>
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<td>Zheng, Ismail &amp; Meng (2014b)</td>
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<tr>
<td>Type 5</td>
<td>$\frac{\text{Accidents}(T_A,Y_A)}{\text{Accidents}(T_B,Y_B)} = \frac{\text{Conflicts}(t_A,X_A)}{\text{Conflicts}(t_B,X_B)}$</td>
<td>Sacchi, Sayed &amp; deLeur (2013)</td>
</tr>
</tbody>
</table>

Notation: $\text{Accidents}(T,Y) =$ expected number of accidents during period $T$ and under conditions $Y$; $\text{Conflicts}(t,X) =$ number of conflicts during period $t$ (much shorter than $T$) and under conditions $X$; $\text{Conflicts}(t,X) =$ number of conflicts of severity $s$ during period $t$ and under conditions $X$; $K =$ conflict-crash conversion coefficient; $K_s =$ conflict-crash conversion coefficient for conflicts with severity $s$; $R_s(X) =$ risk (probability) of crash given risky event of severity $s$; $R(X) =$ risk (probability) of a crash given risky event; $T_A, T_B =$ period of counting crashes before and after improvement, respectively; $t_A, t_B =$ period of counting conflicts before and after improvement, respectively.

$^a$The model’s form is linear $\text{Accidents}(T,Y) = K_s(Y) + K_s(Y) \cdot \text{Conflicts}(t)$, but the authors have estimated different models for different conditions $Y$.

$^b$The model is probabilistic and it estimates the probability of a crash given conflict conditions (true positive).
The Type 3 model involves the concept of conflicts as precipitating events with different probabilities of ‘precipitation’ – collision (Campbell et al., 1996). In this case, a conflict is not a crash and a crash is not a conflict. Formulation of this model was based on an understanding of the crash occurrence mechanism and the model may be considered causal. The model estimates the expected number of crashes in the same period when the precipitating events occur. The mechanism of a collision is well defined, with contributing probabilities of precipitation $R_s(X)$ under various conflict severities $s$ and conditions $X$. Davis et al. (2011) initiated this line of research by reconstructing accidents and applying the counterfactual technique to ‘simulate’ various possible alternative hypothetical developments to estimate the risk of crash as a function of various conditions. This perspective allows considering events aetiologically inconsistent with collisions because the irrelevance of such events is represented in this model with negligible probability of collision. To some extent, this perspective was proposed by Svensson and Hydén (2006) in their proposition of considering events that are not conflicts. This model may be difficult to estimate if the observation period is relatively short. Precipitating events with a high probability of a collision are infrequent and they generally do not appear in a short period. This difficulty may lead to underestimation of the number of crashes.

The Type 4 model defines collisions as being the same type of events as conflicts, assuming the continuity of severity $s$ as it was in the original approach to traffic conflicts presented in Glauz and Migletz (1980), Hydén (1987) and Svensson (1998). This perspective makes estimation of the model easier for short periods without underestimation thanks to extrapolating any observed events into infrequent and severe events including collisions. Campbell et al. (1996) and Songchitruxka and Tarko (2006) proposed using extreme value statistics. Tarko (2012) then presented traffic conflicts as statistical exceedances above a certain threshold of crash proximity $s$. Similar to the Type 3 model, the Type 4 model estimates the number or probability of crashes for the same period when the conflicts were observed. Unlike the Type 3 model, however, the observed events must be aetiologically consistent with collisions and thus should be severe conflicts. The most exciting ability of these models is the possibility of estimating them without crash data (Songchitruxka & Tarko, 2006; Tarko, 2012; Tarko & Songchitruxka, 2005). Recently, Zheng et al. (2014a) confirmed that the exceedances-based estimation is more efficient than that based on extreme values. The same authors used exceedances to estimate the link between the observed conflicts and crashes according to the framework represented by the Type 4 model (Zheng et al., 2014b). The number of crashes predicted in the model may be different
from the number reported by police due to the under-reporting problem and possible inconsistency in the collision definitions applied by police and assumed in the model.

Although the Type 5 model does not have the appeal of the Type 3 and Type 4 models, it is discussed here for its potential usefulness in estimating the so-called crash modification factors that express the relative changes in safety caused by certain treatments. Sacchi et al. (2013) proposed observing traffic conflicts in conditions \((Y_p, X_p)\) before a treatment and in conditions \((Y_A, X_A)\) after implementation of the treatment to estimate the corresponding crash modification factor. In this setting, the change in safety may be attributed to the treatment. Other adjustments may be necessary through control sites. The potential weakness of this model is an implicit assumption that the treatment does not change the relationship between conflicts and collisions. The latter assumption can be defended in cases where the treatment does not obviously affect the risk of failure of the evasive manoeuvre and only affects the probability of the conflict; indeed, it might be in the case of an improved ramp angle as reported by Sacchi et al. (2013), which obviously improved the visibility of vehicles on the major road while its effect on the braking manoeuvre to avoid the collision could be neglected. On the other hand, the relationships of the Type 5 model cannot be applied to study improvements that impact the effectiveness of evasive manoeuvres, such as increasing the pavement friction.

**SPEED SELECTION AND OTHER BEHAVIOURAL MEASURES**

Although traffic conflicts are the most comprehensive surrogate measure of safety, there are other surrogate measures that may be convenient for studies with objectives limited to confirming if a treatment improves safety or selecting the most effective treatment among several alternatives. In such cases, other measures such as speed selection, lane changing, gap acceptance, etc., might be a suitable choice.

The connection between speed and safety is unquestionable although its nature and mechanism are still the subject of research and debate. The large majority of experts agree that high speed and its variance are associated with the increased probability of a crash if all other conditions remain constant. Treatments that change a driver’s speed selection without changing the physical conditions of the road and its environment include speed limits, speed limit enforcement, economic incentives for driving within the speed limit and education about the risk of driving at excessive speed.
The speed–safety relationship becomes complex if a treatment affects the driving environment. Changes to the driving environment that are noticeable to the driver can affect the driver’s risk perception and may cause speed adjustments. For example, drivers reduce their speeds on sharp horizontal curves, but they may ‘undercompensate’ for the added risk; the actual crash risk on a curve thus is still higher than on a straight segment although the speed is lower. This mechanism reverses the expected speed–safety relationship. On the other hand, the idea behind traffic calming is to change the road in a way that increases the perception of hazard or the discomfort of driving at high speed to the point that drivers ‘over-compensate’ for the added risk and the road actually becomes safer. In this case, the speed reduction and increase in safety are observed simultaneously.

It is also possible that the changes in the driving environment are not noticeable to the driver, even if they indeed affect the driver’s safety. For example, modifying traffic signal coordination in order to reduce arrival time at the next intersection when stopped vehicles are still present there may reduce rear-end collisions. This improvement is not obvious to drivers and thus it may not affect their perception of risk; drivers will not be tempted to reduce their speed or the distance to other vehicles in front of them. In this case, any behaviour-based measure cannot serve as a surrogate measure of safety.

Fig. 4 presents the connection between behaviour, environment and safety. A good behavioural measure, such as free-flow speed, is a convenient surrogate measure of safety if the studied treatment does not affect the road and other components of the driving environment. Otherwise, the relationship between speed and safety is unclear; therefore, relying solely on driver behaviours may be misleading.

Strong statistical evidence of the relationship between the mean speed and safety was provided by Nilsson (2004), who proposed a power model to describe the relationship between the relative change in the mean speed and the crash frequency. This model was re-estimated with meta-analysis by Elvik, Christensen and Helene Amundsen (2004) and then Elvik (2013).
The authors emphasised that the relationship holds when confounding factors are controlled for. Keeping the cofounding factors of speed, such as road geometry or weather, constant is consistent with the preceding discussion of the conditions required for the validity of the speed–safety relationship. The most recent adjustment of the model was described in *Elvik (2013)*. The meta-analysis applied to a large number of studies pointed to the exponential function rather than to the power function as a better representation of the speed–safety relationship. Nevertheless, the estimated relationships varied strongly across individual studies; in many cases the relationship was even reversed (negative exponent). The presence of not-fully controlled conditions external to drivers could be the source of this result, together with many other potential causes. Many authors have statistically connected detector-measured traffic characteristics with the risk of collision (e.g., *Abdel-Aty, Hassan, Ahmed, & Al-Ghamdi, 2012; Abdel-Aty, Uddin, Abdalla, Pande, & Hsia, 2004; Hossain & Muromachi, 2011; Hourdos, Garg, Michalopoulos, & Davis, 2006; Oh, Oh, & Ritchie, 2005; Pande & Abdel-Aty, 2006; Xu, Tarko, Wang, & Liu, 2013*). Unlike the already discussed long-term impact of the average speed on safety, this relationship is short term, and it reflects the safety impact of dynamic interactions between vehicles manifested via temporal and spatial speed variability.

**COMPUTER SIMULATION OF SAFETY**

Existing computer simulation models have been developed for studying traffic performance at individual roads and in road networks. They are indispensable in estimating speeds, delays and other performance measures for new road systems. These models adequately represent typical, or standard, traffic events that frequently occur, are observed and are well understood. The essence of traffic safety lies in the dangerous and infrequent interactions that are difficult to observe and study, and their nature therefore is not as well understood as the other more frequent events. Crashes are not intended to occur in the existing computer simulation models. The near-miss events may occur incidentally, but very little can be learned about safety on a simulated road. *Gettman et al. (2008)* and *Archer (2005)* investigated the potential use of microscopic simulation to model traffic conflicts. The results from recent attempts to use the existing simulation tools, such as VISSIM, indicate an evident correlation between simulated interactions and traffic conflicts observed in the field and even collisions reported by police (e.g., *Gettman et al., 2008; Huang, Liu, Yu, & Wang, 2013; Ozbay, Yang, Bartin, & Mudigonda, 2008*). With the limitations of the current simulation models the reported correlation
might be introduced by the exposure. Roads with heavy traffic tend to have more crashes and traffic interactions than roads with low traffic regardless of whether these interactions are simulated or observed.

The progress in measurement techniques and gaining a better understanding of dangerous interactions engendered by on-going research on traffic conflicts should allow proper simulation of more and more risky events. This knowledge is currently scant but will grow with the progress in analysing naturalistic driving and roadside measurements. With the growing knowledge of dangerous interactions, the existing models will be supplemented with components that properly represent the possibility of driver errors and the ensuing response to the near-collision situations under various conditions. The initial simulation-based models may combine simulation of traffic conflicts and the statistical components of the risk of collision conditioned on these conflicts. With the growing understanding of near-collision interactions more severe conflicts could be simulated up to the point of eliminating the statistical component.

**CONCLUSIONS**

In general, the surrogate measures of safety can be classified into several categories that include conflicts, behaviours, specific conditions and derivatives thereof. The most comprehensive measure is traffic conflicts, if properly defined and observed, because their occurrence is caused and their probability is affected by most of the conditions (factors) that affect the occurrence and probability of collisions. A properly defined traffic conflict is the one caused by human error. The closer the conflict is to the corresponding collision, the more aetiologically consistent the two are. The minimum TTC observed during the conflict process seems to be an appropriate measure of collision nearness in most cases. The minimum distance to collision with simultaneous consideration of the speeds and travel directions of the interacting vehicles might provide the most universal measure of collision nearness. The observation period to collect a sufficient number of conflicts is much longer than the period recommended in the existing traffic conflict techniques. Maturing measurement technologies will help achieve a practical method of observing traffic conflicts in extended periods without expensive human involvement.

Among several methods of estimating the connection between conflicts and collisions, the count or probabilistic models seem to promise the quickest road to practical results. To fulfil this promise, these models must include traffic conflict’s other variables that affect the probability of the collision given the conflict. The biggest hurdle in estimating these models is the necessity of
using crash data with their disadvantages and much longer observation periods necessary to observe traffic conflicts.

Exceedance models are the only models that can be estimated without crash data. They return the probability of collision given the conflict and, together with the known frequency of conflicts, they return the expected number of crashes during the period when conflicts were observed. The road to practical results is longer than the traditional count and probabilistic models. More research is needed to confirm the usefulness of these models and to advise the best data collection and model estimation methods.

Recent studies point to traffic conflicts as potentially useful for estimating the so-called crash modification factors. These factors are essential in predicting the safety benefits of various road and traffic control countermeasures. This approach may produce biased results if the evaluated treatment affects the probability of collision given the conflict.

Behaviour-based surrogate measures of safety, such as speeds or car-following headways, are useful if the studied treatment does not change the road and its environment, but rather directly changes driver behaviour. Otherwise, the risk compensation behaviour may skew the results considerably. Power and recently exponential relationships between speed and safety have been reported in the literature (Elvik, 2013).

Simulating road safety has advanced gradually at a pace determined by the growing knowledge of driver behaviour and performance during near-collision events. As this knowledge continues to grow existing models will be supplemented with components that properly represent the possibility of driver errors and responses to near-collision situations under various conditions. It seems that the road to simulating safety without resorting to statistical relationships will be a long one. Hybrid models that include simulation and statistical components offer a less remote and more practical solution. The current surrogate measures of safety research may deliver the two elements of hybrid models: improved simulation of conflicts and a statistical bridge linking conflicts with collisions.

REFERENCES


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METHODS FOR EVALUATING SAFETY IMPACTS OF COUNTERMEASURES