**Review of Surrogate Safety Measures for Roadway Safety Analysis**

**Figure 3 is NOT his. Needs permission!**

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**Abstract**

Vehicular collisions are a source of tremendous cost in the form of financial damages, human injuries, and deaths. Because of this, traffic safety is of utmost importance to engineers as they design transportation infrastructure. Traffic safety analysis informs decisions relating to projects intended to bolster the safety of roadways and intersections, and this analysis uses data that is collected for a transportation system network. The traditional method of safety analysis uses collision data, but a newer set of safety analysis methods instead considers data on traffic conflicts as a replacement for collisions. These methods are known as surrogate safety measures (SSMs) which analyze kinematic data to assess safety. Several SSMs have been developed and validated in an effort to capture the risk exposure of vehicles more fully. SSMs offer a range of benefits over traditional analysis with collision data. First, the data used by SSMs may be collected more rapidly than collision data. Collisions happen quite infrequently from a data collection standpoint, but vehicular kinematic data may be collected in large quantities within a matter of weeks. Second, surrogate safety measures are a proactive analysis, as they allow for safety analysis without collisions occurring. Improvements may be made based upon the results of an SSM analysis to prevent crashes. Third, kinematic data supplies so many more data points as opposed to collisions that statistical analysis for traffic conflicts is significantly more robust. Analysis with SSMs has evolved over the decades from being measured with manual observations in the field and use of time-lapse imagery to use of microsimulation software, with the most recent advancement being the incorporation of connected vehicle data. This paper serves as a summary of the development of SSMs and establishes the state of the practice for surrogate safety analysis.

**Introduction**

Surrogate safety measures (SSMs) are a means of measuring the safety of traffic infrastructure using data other than crash data. SSMs are beneficial because they eliminate the need to wait a long time for crashes to occur to generate data. In a similar vein, use of SSMs allows for hazardous areas to be identified prior to a large number of crashes occurring. This may mean that improvements can be made earlier to prevent those crashes. Yet another benefit of using SSMs is the dramatic increase in data points that comes from being able to analyze traffic conflicts instead of collisions. Conflicts are extremely common; whereas collisions are quite rare by comparison for an individual location. More data points allow statistical analysis to be more effective.

One class of current research pertaining to SSMs involves the investigation of harsh braking events recorded by connected vehicles as an SSM. The validity of harsh braking as an SSM will need to be investigated in order to determine if its use is indeed viable. Such validation may be done through the comparison of results of a safety analysis conducted with the harsh braking SSM to historical crash counts or to the results of a safety analysis conducted using existing SSMs. The articles and reports included within this paper offer insight into how SSMs have evolved over time and how new SSMs may be validated. Similarly, they illuminate the various mechanisms used to compute the safety of road infrastructure as alternatives to crash data.

The following sections provide summaries of pertinent content within a selection of articles and reports published on SSMs in transportation engineering. The literature reviewed includes a paper that uses SSMs in conjunction with connected vehicle data, papers that define SSMs founded in both kinematics and statistics, papers on the use of SSMs with traffic microsimulation software, and even two papers that establish new SSMs and validate them through the use of microsimulation (Wang & Stamatiadis, 2013; Astarita et al., 2020). This information is presented together in one paper to be a resource for researchers and practitioners alike to understand the current state of this research and the means by which these methods have been established.

**Paper #1: “Analysis of Traffic Conflicts and Collisions”**

The first paper considered was written in 1978 by Brian L. Allen, B. Tom Shin, and Peter J. Cooper of McMaster University in Canada. These researchers set out to improve upon the previously established traffic conflicts technique (TCT). They outline a number of flaws with TCT and propose several SSMs that would ameliorate the shortcomings of TCT as it existed previously. Their newly established SSMs include proportion of stopping distance, gap time, encroachment time, deceleration rate, post-encroachment time, and initially attempted post-encroachment time (Allen et al., 1978).

The paper begins with the discussion of the existing TCT and the areas in which it lacks effectiveness. Prior to this paper, TCT used brake applications as the primary indicator of a traffic conflict. While brake applications are easily identified and counted without subjectivity in the data analysis process, they have several drawbacks. Drivers have variable braking habits with overly cautious drivers applying brakes when it is not necessary and less cautious drivers failing to apply brakes during hazardous encounters. Brake applications are also a binary measurement with no indication of the severity of the evasive maneuver. Finally, deceleration is not always an effective evasive maneuver. Sometimes acceleration is the safest option in order for a vehicle to clear a potential collision location. This can lead to an inaccurate conclusion in TCT. A traffic conflict definition can be misleading if it relies on the presence of an evasive maneuver, such as brake application. This is because collisions can occur without any evasive maneuver taking place. This means that a traffic conflict definition requiring evasive action can lead to collisions that are not preceded by a conflict. This is problematic because collisions are supposed to be a subset of conflicts. Figure 1 illustrates a left-turning vehicle and a through vehicle in conflict, with points in space and time indicated which are significant to this interaction. Allen et al. (1978) suggest that measurement of various parameters within the time-space diagram would be useful for safety analysis, and they present several measures which they developed.



Figure 1. Time-Space Diagram of a Left-Turn Conflict

The paper outlines SSMs developed by Allen et al. (1978) as alternatives to TCT based primarily on brake applications. The first measure is proportion of stopping distance (PSD), which is the ratio of the remaining distance between a vehicle and a potential collision point to the minimum acceptable stopping distance. The PSD must be at or above a value of 1.0 for a situation to be safe. It may be found with equations 1 and 2, in which *RD* is the remaining distance between a vehicle and a potential collision point, *MSD* is the minimum acceptable stopping distance, *V* is the following vehicle’s velocity, and *D* is the maximum acceptable deceleration rate (Allen et al., 1978).

 (1)

 (2)

The next measures described are gap time (GT), encroachment time (ET), and deceleration rate (DR). GT is the difference between T3 and T2 in Figure 1. Time T3 is the time at which a through vehicle would have arrived at the potential collision point if the through vehicle had not altered its motion. Time T2 is the time at which the left-turning vehicle is no longer encroaching on the through vehicle’s path of travel. GT can therefore be positive or negative. A smaller absolute value of GT represents a greater probability of a collision occurring. ET is a measure of the total amount of time that the left-turning vehicle occupies the path of travel of the through vehicle, the difference between T2 and T1 in Figure 1. DR is another SSM which occurs through the development of a conflict and is capable of indicating situational severity. Allen et al. (1978) point out that variability between drivers can account for higher or lower DRs to some extent. However, rapid deceleration is a strong indicator of a hazardous situation.

The last two developed measures are: post-encroachment time (PET) and initially attempted post-encroachment time (IAPE). PET is the amount of time that elapses between when an encroaching vehicle leaves the path of travel of another vehicle and when the other vehicle reaches the point where a collision would have occurred. PET may be quantified as the difference between T4 and T2 in Figure 1. PET represents how narrowly drivers avoided colliding. The measure represents the cumulative effects of the initial situation and the actions taken by the drivers to avoid colliding. PET suffers from drivers often accelerating as soon as a conflict ends. For this reason, Allen et al. (1978) developed IAPE which eliminates the effects of early acceleration. IAPE may be calculated with equations 3 and 4, in which *T1* is the beginning time of encroachment, *P1P3* is the distance between the potential collision point and the initial location of the through vehicle, and *V2* is the average through vehicle velocity.

 (3)

 (4)

Allen et al. (1978) suggest that the most controversial part of their paper is the rejection of the TCT brake application method. They concede the point that their evaluation of their new SSMs is not highly effective in confirming an advantage in these measures. This is because the correlation coefficients obtained for the SSMs were low in spite of an active collision history at the study intersection. Little hope exists to have higher correlation coefficients at any intersection. Low correlation coefficients may be something to be expected, and arguments for a transition away from brake applications should rely on the conceptual weaknesses of brake applications. The fact that not all collisions are preceded by braking should alone bar brake application from being an acceptable measure (Allen et al., 1978).

**Paper #2: “Extended Time-to-Collision Measures for Road Traffic Safety Assessment”**

The next article, by Michiel M. Minderhoud and Piet H.L. Bovy and published in 2001 in the journal *Accident Analysis and Prevention*, outlines the development of two new modifications to a surrogate safety measure known as time-to-collision (TTC). Minderhoud and Bovy (2001) call these modifications “Extended Time-to-Collision” together, and individually these modifications are called “Time Exposed Time-to-Collision” and “Time Integrated Time-to-Collision.” The paper addresses the use of these measures with vehicles that are equipped with autonomous intelligent cruise control (AICC). These new measures are intended to provide a comparative measure which may be used in conjunction with microsimulation to understand the impacts to safety of the use of AICC.

Minderhoud and Bovy (2001) describe the TTC SSM. TTC is the amount of time that would need to elapse in order for two vehicles to collide if their trajectories remain unchanged. TTC may be calculated with equation 5, in which *X* is the vehicle’s position, *X’* is the vehicle speed, and *l* is the vehicle length. The leading vehicle is denoted as *i-1*, and the following vehicle is denoted as *i* (Minderhoud & Bovy, 2001).

 (5)

TTC may only be calculated for situations in which the speed differential between the vehicles is such that the leading vehicle is traveling more slowly than the following vehicle. The safety of a TTC value is tied to a critical TTC safety threshold. TTC values above this threshold are safe situations, and TTC values beneath this threshold are unsafe. Past research has produced threshold values ranging from 2.6 seconds to 4 seconds (Minderhoud & Bovy, 2001).

Minderhoud and Bovy (1978) present their modifications, beginning with time exposed time-to-collision (TET). TET is a summation of the time that the TTC is beneath the safety threshold value. A low TET value indicates a safe situation because the overall exposure to a hazardous situation is small. It does not consider how severely the safety threshold is being violated. Calculation of TET requires position and speed data for all vehicles on a road section within the study time period. This data is typically collected at discrete moments, separated by a time scan interval. TET may be calculated with equation 6, in which *TTC*\* is the safety threshold value of TTC, *TTCi(t)* is the value of TTC at a discrete time *t* for vehicle *i*, δ*i(t)* is a switch variable that indicates if the threshold TTC is exceeded, and τ*sc* is a time scan interval indicating the time step resolution. For a N number of drivers, the population TET\* may be found with equation 7 (Minderhoud and Bovy, 2001).

 (6)

 (7)

Next, the paper presents the time integrated time-to-collision (TIT) SSM. The TIT measure addresses one drawback of the TET metric, its inability to consider the amount by which the safety threshold TTC is not met. In this way, TIT is capable of capturing the severity of the hazard better than TET. TIT may be calculated for continuous time with equation 8. Analysis using continuous time is not practically possible, so equation 8 represents a theoretical abstraction. For discrete time, TIT may be calculated with equation 9 (Minderhoud & Bovy, 2001). Figure 2 presents a TTC profile which illustrates both the TET and TIT measures.

 (8)

 (9)



Figure 2. Illustrations of TET and TIT

Minderhoud and Bovy (2001) use the comparative power of TET to demonstrate the impact of incorporating various levels of AICC. AICC is capable of adapting vehicle speed to keep proper distance from leading vehicles. To analyze the effectiveness of AICC, the researchers used an applied microscopic simulation with an individual driving behavioral model. They ran models for 50% partial AICC, 100% partial AICC, 50% complete AICC, and 100% complete AICC. Their analysis was also done for 1 second, 2 second, and 3 second safety threshold TTC values. They suggest that a shorter safety threshold TTC is possible for AICC because of its increased reaction ability over humans. Partial AICC requires driver intervention at speeds below 30 km/h or when the necessary deceleration is at or above 3 m/s2. Complete AICC supports the driver fully. Again, there was high exposure to high TTC values and low exposure to small TTC values. Choice of threshold TTC value has a large effect on the total exposure time. Choice of a realistic threshold depends upon the design of the AICC system and will need to wait until AICC systems are more established and empirical data is available. This may eventually be accomplished in future research.

**Paper #3: “Surrogate Safety Measures from Traffic Simulation Models – Final Report”**

This report, written in 2003 by Douglas Gettman and Larry Head, is a summary of a project by the Federal Highway Administration which sought to evaluate the efficacy of the use of simulation software in conjunction with SSMs to determine the safety of intersections. It also identifies algorithms for determining SSMs from simulation models, known as the Surrogate Safety Assessment Methodology. This methodology allows for evaluation of various alternatives and is applicable to both signalized and unsignalized intersections.

Gettman and Head (2003) present descriptions of the following SSMs that are a part of the traffic conflicts technique: GT, ET, DR, PSD, PET, IAPE, and TTC. Field measurement is possible for these measures, but it introduces subjectivity which can compromise the quality of the safety analysis. Microsimulation can be used to simulate conflicts more precisely. There are other SSMs that have also been suggested. These measures include “delay, travel time, approach speed, percent stops, queue length, stop-bar encroachments, red-light violations, percent left turns, spot speed, speed distribution, and deceleration distribution” (Gettman & Head, 2003). Although these measures have not been quantitatively related to crash frequency, they may be used as indicators of higher or lower crash frequency. These informal measures exist for two-lane roads as well and include design features such as curvature and superelevation (Gettman & Head, 2003).

The report gives an overview of traffic simulation models. Microsimulations analyze traffic at the level of the individual vehicle over time steps. Vehicles in the simulation have varying characteristics, but they always drive safely and never crash. Gettman and Head (2003) favor microsimulations that are commonly used in industry and have analyses that are simple to implement. They also prefer the simulation to have a graphic network editor and analysis tools that may be used after processing. The analysis must model driver behaviors such as car following, lane changing, and gap acceptance and should have particularly realistic behavioral components to be useful. Most microsimulation programs do not readily allow extraction of data to output files, but this would be necessary for computing SSMs. The behavior and driver performance parameters need to be able to be manipulated, and the ability for a user to make or request modifications to the software itself at a relatively low cost is preferable. With these preferences established, Gettman and Head (2003) evaluate nine microsimulation programs: CORSIM, VISSIM, Simtraffic, Paramics, HUTSIM, Texas, WATSIM, Integration, and AIMSUN.

The evaluation of the various microsimulation software programs did not identify any clear best choice and revealed that using any microsimulation program for the computation of SSMs would require at least some modification of the program. Because of this, Gettman and Head (2003) recommend using a surrogate safety assessment module (SSAM) after the simulation is run. The workflow for conducting a safety analysis would involve running a simulation model, importing event files to the SSAM from the simulation, and then running the SSAM to generate reports and graphics detailing the computed SSMs. Gettman and Head (2003) go on to outline algorithms which allow SSMs to be computed for conflict events. Conflict events that may be modeled include crossing flows, merging crossing flows, adjacent flows (lane changing), and following flows (rear-end collisions). Some conflict events that are not modeled are sideswipe, head-on, and swerve-out-of-lane collisions as well as U-turn related and pedestrian collisions. Gettman and Head (2003) call for future research to improve the modeling of pedestrian collisions.

The report concludes with a discussion of validating SSMs as computed from microsimulations. One method of validation is determining if an SSM analysis with microsimulation may be used to decide between two different intersection design alternatives. The next way is to determine a correlation between SSMs and traditionally gathered crash data. The goal here is to determine if an SSM analysis with microsimulation may be used to replace traditional data gathering procedures. The third way suggested by Gettman and Head (2003) to validate SSMs is to determine if it is possible to predict the benefits to safety caused by the implementation of safety-oriented intersection improvements. The report outlines methods for validating SSMs with microsimulation in these ways.

**Paper #4: “Comparing Safety Performance Measures Obtained from Video Capture Data”**

This paper, written in 2010 by Giuseppe Guido, Frank Saccomanno, Vittorio Astarita, Demetrio Festa, and Alessandro Vitale and published in the *Journal of Transportation Engineering*, details a study in which SSMs were calculated for a roundabout in an urban area of Cosenza, Italy. The SSMs used in this study include TTC, TIT, deceleration rate to avoid collision (DRAC), PSD, and crash potential index (CPI). The different outcomes of the safety analysis according to the particular safety measure used, traffic conditions, and roundabout geometry variations are discussed with the purpose of demonstrating the usefulness of SSMs and highlighting the impact of using different measures on the outcome of safety analysis (Guido et al., 2010).

Next, Guido et al. (2010) discuss the SSMs that they use in this study. The first SSM described is DRAC. DRAC is based on the idea that a leading vehicle will execute some initial action such as braking, changing lanes, or accepting a gap. The following vehicle, in turn, decelerates in order to avoid a rear-end collision. Guido et al. (2010) use a DRAC safety threshold of 3.35 m/s2. DRAC is an effective safety measure because it considers the effects of differential speeds and evasive action in the form of braking. It may be calculated for rear end collisions using equation 10, in which *t* is the time interval, *X* is the position of the vehicle, *L* is the vehicle length, and *V* is the velocity. The subscript *FV* refers to the following vehicle, and the subscript *LV* refers to the leading vehicle.

 (10)

Guido et al. (2010) next discuss TTC and PSD as defined previously. We have seen the definitions of TTC and PSD before. The safety threshold for TTC was set at 1.5 seconds in this paper. The paper goes on to define and discuss TIT, which we have seen in the discussion of Paper #2.

The final SSM discussed in the paper is CPI. CPI was developed in response to the identification of concerns with the original DRAC measure. DRAC has the drawback of not considering the variability of vehicle braking capacity based on mechanical variations in vehicles or environmental factors. To address these variations, the CPI was developed, which takes braking capacity variations into consideration. The DRAC and the maximum available deceleration rate, MADR, are calculated at every time step considered. CPI may be calculated using equation 11, in which Δ*t* is the observation time interval, *b* is a state variable which equals 1 if the gap between the leading and following vehicles is closing and 0 otherwise, *Ti* is the total observed time for vehicle *i*, *tii* is the initial time interval observed, and *tfi* is the final time interval observed (Guido et al., 2010).

 (11)

The paper goes on to outline the methods employed to measure the interactions of vehicles within the study roundabout. A camera was set up on the roof of a close building and was used to record traffic operations on a weekday during off-peak hours. Off-peak hours were selected because the vehicular speeds are not reduced by congestion. Radar measurements revealed the average speed of vehicles to be 25 kph during the off-peak conditions. The Adobe Premier software program was used to process the video to obtain trajectories. In addition to the video footage, 176 virtual detectors were spaced 1 meter apart to collect individual trajectories. Following and leading vehicle trajectories were then linked, resulting in 77 pairs of vehicles. Guido et al. (2010) verified the values they estimated for vehicle speeds by measuring speeds with laser guns and comparing the results. Laser guns were set up at six reference stations, including four stations at the roundabout entrances/exits. A statistical analysis of the speeds calculated from the video footage and the speeds measured using the laser guns revealed that no statistically significant difference exists between the two methods of measuring vehicle speed.

The paper next details the computation of SSMs from the 77 identified interactions. For CPI, two values were used for the MADR. The first definition is based on the coefficient of friction and cross grade of the pavement. The second definition is based upon a truncated normal distribution with a minimum value of 4.2 m/s2 and a maximum value of 12.7 m/s2. Potential conflicts are defined as interactions with a DRAC exceeding 3.35 m/s2, a TTC lower than 1.5 seconds, a PSD less than or equal to 1, a TIT greater than zero, or a CPI greater than zero. Guido et al. (2010) used a standardized U-statistic to compare the safety measures. This statistic was calculated using equation 12, in which *x* is the observed exposure time to a conflict value, *xmin* is the minimum observed exposure time to a conflict value, and *xmax* is the maximum observed exposure time to a conflict value.

 (12)

The paper concludes with a discussion of the characteristics of the SSMs that were highlighted in this study. Guido et al. (2010) found very similar results with TIT and TTC in the safety analysis. PSD resulted in a higher time exposure to hazardous situations and nebulous results as to where safety problems exist. Guido et al. (2010) found similar results for both of the CPI measures; although the CPI using the distributed MADR led to more localized results. Relative to other measures, CPI underestimated risk possibly due to CPI’s consideration of braking capacity. The measures all identified areas with significant merging activity. This exposes vehicles to more abrupt acceleration and deceleration rates as well as traffic flow turbulence. Overall, the study revealed that measures which require a larger number of inputs, such as CPI, yielded more focused results regarding locations of safety hazards. These more focused results may potentially be of greater use to decision-makers in determining which safety improvements ought to be prioritized.

**Paper #5: “Comparing Simulated Road Safety Performance to Observed Crash Frequency at Signalized Intersections”**

This 2011 paper was written by Janailson Souza, Marcos Sasaki, and Flávio Cunto, Ph.D. and was submitted to the International Conference on Road Safety and Simulation. The paper details a study in which the researchers conducted one of the validation efforts suggested in the FHWA report, namely validation by correlating SSMs and traditionally gathered crash data. The study considered intersections in Fortaleza, Brazil, and the comparison of simulation results with real-world data was done for both peak and off-peak two-hour periods. The SSMs evaluated in this paper include TTC, DRAC, and CPI. The number of rear-end collisions was observed to decrease over a period of approximately three years (2007, 2008, and 2009), but the SSMs as computed with microsimulation programs did not reflect this decrease (Souza et al., 2011).

Souza et al. (2011) state that SSMs fall into three categories: time-based measures, measures of required braking power, and safety indices. All of these categories serve to provide a proactive approach to safety analysis. Another benefit of SSMs over crash data is the significantly greater frequency of high-risk situations in comparison to crashes which means that statistical methods are more reliable. Souza et al. (2011) point out a limitation in time-based measures in that multiple scenarios may result in the same value. For instance, a low speed at a close following distance may have the same TTC as a high speed at a longer following distance. This makes it difficult to use time-based measures effectively to determine crash severity. For this reason, measures of required braking power and safety indices can be more useful. Souza et al. (2011) consider one measure from each category (TTC, DRAC, and CPI). The researchers used the geometric and traffic characteristics of three intersections to build six scenarios in PTV VISSIM: peak and off-peak models for each of the three intersections.

The results of the simulation include numbers of conflicts over a three-year period and the number of conflicts per vehicle over a three-year period. The results are for three years so that they may be compared to the crash data from 2007, 2008, and 2009. The crash data exhibits a downward trend over the three-year timespan which is not predicted by the SSMs. Souza et al. suggest that the simulation environment’s simplicity and the rareness of collisions may account for this discrepancy. The TTC and DRAC measures resulted in a much higher number of conflicts than CPI did. CPI also exhibited the highest variability which is due to the inclusion of two stochastic components: random seed generation and a distribution of maximum available deceleration rates. Crashes and conflicts increase with increased traffic volume, and the three-approach intersection in the study had significantly fewer conflicts and collisions than the other two intersections with four approaches. This supports the idea that increased exposure increases conflict and crash numbers (Souza et al., 2011).

The paper concludes with ideas regarding the correlation of the SSMs with actual crash data. In spite of the microsimulation not capturing the downward trend in collisions, the SSMs did find the differences in the numbers of crashes at each of the three intersections considered. This suggests that microsimulations may be used for proactive safety analysis. Souza et al. (2011) suggest further research in incorporating parking maneuvers in safety analyses and including more types of vehicles, such as motorcycles which were excluded from this study. Another potential research area is the use of safety performance models to improve crash estimates.

**Paper #6: “Use of Crash Surrogates and Exceedance Statistics to Estimate Road Safety”**

This 2012 article was written by Andrew P. Tarko at Purdue University and published by the journal *Accident Analysis and Prevention*. The article presents a new type of safety model which is a combination of multiple previous safety models and expands the narrow abilities of existing models. Tarko writes that the narrow abilities of prior models are due to the use of poor-quality data to estimate complicated safety factors. Data quality has improved because of better sensing techniques and technology and naturalistic driving data collection. The new model presented in this article improves upon past techniques by including crash precursor events into an estimation method that makes use of the Generalized Pareto distribution (Tarko, 2012).

The paper begins with an overview of past methods for determining what events should be classified as traffic conflicts. A pyramid may be used as a representation of the frequency of traffic interactions based on their riskiness level. The pyramid is broken into sections representing, in order of increasing riskiness level: undisturbed passages, potential traffic conflicts, light traffic conflicts, serious traffic conflicts, and collisions. Less risky interactions comprise larger portions of the total area of the pyramid than riskier interactions, indicating the higher frequency of less risky interactions. This representation is illustrated in Figure 3 (Tarko, 2012).



Figure 3. Pyramid Representation of Traffic Interaction Frequency

Tarko (2012) then proposes an approach to developing a better model for traffic interactions. The article defines *n* number of traffic interaction classes. The assumptions for this model are that the interaction severity is continuous, an event belongs to a particular interaction class if its severity is above a particular threshold, and the distribution of the severity of events has a right tail that converges to zero. The collision proximity, in turn, may be determined by finding the difference between the event severity and the collision severity threshold.

Tarko (2012) explains that this model is an exceedance distribution which may be used in conjunction with the Extreme Value Theory. An equivalent form of the generalized extreme values distribution is the Generalized Pareto distribution which is applicable to values in exceedance of a large fixed threshold. This distribution, and the Extreme Value Theory in general, has been used in areas concerning safety analysis, such as natural disasters, financial losses, and engineering failures. According to Tarko (2012), the generalized extreme values and Generalized Pareto distributions may be used to estimate how frequently a car will depart from a roadway. The riskiness of events is broken into the following categories: all events, risky events, and actual road departures which may or may not be crashes. A fourth category, representing crashes following road departure, may be incorporated into a complete safety model.

Tarko (2012) defines some terms including *threshold*, *risky* *event* *range*, and *event* *severity*. The threshold of a risky event is the lateral clearance below which a driver would feel uncomfortable. The risky event range is the longitudinal distance over which a vehicle is too close to the edge of the road and signifies the distance required for a driver to become uncomfortable and make a corrective motion. Event severity is the proximity of a risky event to an actual road departure and is useful for fitting the Generalized Pareto distribution.

The article outlines experiments conducted with a driving simulator and four test drivers. The track in the simulator featured many horizontal curves as well as accurate signing, billboards, a realistic rural background landscape, and traffic traveling in the same direction as the driver. The test subjects drove 2,052 miles, departing the road four times and experiencing 2,500 risky events. Using the bootstrap method, Tarko (2012) found ninety percent confidence intervals for road departures based on the number of risky events. The actual number of road departures was not used in the determination of these confidence intervals but did fall within the interval, which gives credence to the intervals and the methods used to find them. Tarko (2012) developed models for the probabilities of risky events, crashes, and crash severity as well as a model that computes the frequency of collisions of varying severity levels. Tarko’s models are SSMs, taking data other than crash data and producing crash count and risky event count estimates. The consideration of the breakdown of collision severity is a valuable contribution to the literature on SSMs. Tarko (2012) calls for subsequent research into application of Pareto models to suitable data. Pareto models could potentially be used in conjunction with connected vehicle data or data from microsimulation software to determine the expected crash frequency along roadways.

**Paper #7: “Surrogate Safety Measure for Simulation-Based Conflict Study”**

This paper by Chen Wang and Nikiforos Stamatiadis was published in the journal *Transportation Research Record* in 2013. It outlines the development of an SSM called the aggregated crash propensity metric (ACPM), which may be used with microsimulation software programs to evaluate intersection safety. Wang and Stamatiadis (2013) also describe a probabilistic model which was developed to incorporate the distributions of driver reaction times and deceleration rates during braking. This serves to compute the probability of crashes which fit into three categories: rear-end, crossing, and lane change. The measure was validated using VISSIM models which found that the ACPM performs better than the Highway Safety Manual methods in determining the relative safety of intersection designs. Attempts to correlate ACPM with real crash data was in its early stages at the time this paper was published, but the early findings suggest the potential for ACPM to be used to predict actual crash numbers.

The article begins with a discussion of SSMs and the apparent need for a new metric which more fully uses the detailed data produced by microsimulations. According to this paper, SSMs have not grown in complexity sufficiently with advancements in microsimulation. The SSAM, for instance, uses TTC with an arbitrary threshold of 1.5 seconds to measure safety. Wang and Stamatiadis (2013) intend to bridge the gap with the ACPM.

The ACPM measures the probability for each conflict at an intersection to result in a collision while considering human and vehicular variations. For every conflict, there exists a portion of the driver population that has a reaction time longer than the TTC, and there exists a portion of vehicles that have a maximum available braking rate that is lower than the required braking rate. The reaction time distribution is a lognormal distribution with parameters that depend on the type of collision (crossing, lane-change, and rear-end). The maximum available braking rate distribution is a truncated normal distribution with a mean of 9.7 m/s2, a standard deviation of 1.3 m/s2, a lower limit of 4.2 m/s2, and an upper limit of 12.7 m/s2, as determined in prior research (Wang & Stamatiadis, 2013). These distributions are illustrated in Figures 4 and 5.



Figure 4. Reaction Time Distribution with TTC



Figure 5. Maximum Available Braking Rate Distribution with Required Braking Rate

The groups created by the graphs shown in Figures 4 and 5 are used to determine the crash propensity metric and ultimately the ACPM. Drivers in group A do not react in time to avoid a collision. Drivers in group B-2 react quickly enough to initiate an evasive maneuver but are unable to perform the evasive maneuver successfully due to vehicular limitations. The sum of these groups (A and B-2) are all the conflicts that will result in a collision. The probability of a collision for an individual conflict is the crash propensity metric, and the sum of all propensity metrics for conflicts within a particular category is the ACPM (Wang & Stamatiadis, 2013).

The required braking rate is derived for each of the three types of collisions using kinematics. Wang and Stamatiadis (2013) derived equations in which *li* and *wi* are the length and width of vehicle *i*, *Vi* is the velocity of vehicle *i*, *D* is the distance between conflicting vehicles, *θ* is the conflict angle, and *x* is the reaction time. Equations 13 and 14 are for crossing conflicts. Equation 13 calculates the total time *t* during which the leading vehicle is at the conflict point. Equation 14 finds the required braking rate for a crossing conflict and uses the output of equation 13. For rear-end conflicts, equation 15 may be used find the required braking rate, and, for lane change conflicts, equation 16 may be used to find the required braking rate.

 (13)

 (14)

 (15)

 (16)

The crash propensity metric illuminates the differences between two scenarios which may appear identical when looking only at the TTC. In two scenarios with an identical TTC, the required braking rates may be quite different. This makes one scenario more likely to result in a collision, and the crash propensity metric will indicate just how much more likely it is (Wang & Stamatiadis, 2013).

The researchers validated the ACPM using experimentation with VISSIM models of twelve intersections on three arterials in Kentucky. The ACPM was computed for each of the three collision types at all of the intersections. The total ACPM is the sum of the three collision type-specific ACPM values. Wang and Stamatiadis (2013) ranked the intersections according to their relative safety according to the ACPM and then predicted the annual numbers of crashes at each of the intersections using the methods presented in the Highway Safety Manual. Spearman rank tests showed high rank correlation coefficients, indicating that the ACPM is a good indicator of relative intersection safety. The researchers also used the leave-one-out cross-validation method to test the ability of the ACPM to predict crash numbers at each of the intersections. The actual crash numbers fell within the 95% confidence interval of the crash predictions most of the time, indicating that ACPM is promising for use as a crash predictor.

Wang and Stamatiadis (2013) conclude the paper by reiterating that the ACPM is an SSM to be used for determining the relative safety of transportation infrastructure. The metric successfully determines the probability of crashes using TTC without an arbitrary cutoff value, a weakness of previous use of TTC. Wang and Stamatiadis (2013) point out that VISSIM’s simulation operates based on the assumption that all drivers will follow the rules regarding right-of-way. Of course, this is not always the case and may lead to crossing conflicts being underrepresented. Practitioners may benefit from using another method to characterize crossing conflicts.

**Paper #8: “Identifying High Crash Risk Roadways through Jerk-Cluster Analysis”**

This paper is a thesis written by Seyedeh Maryam Mousavi and submitted to the Louisiana State University in 2015 as part of the requirements for a master’s degree. It details a study in which Mousavi (2015) uses naturalistic driving data from GPS sensors to identify locations in which high concentrations of abnormal driving events occur and correlate crash rates to these abnormal events. These events involve sudden and unusual movements of vehicles that may be detected through a measurement of the vehicle’s first derivative of acceleration, known as jerk. Mousavi (2015) mentions the importance of this work as a means of computing estimates for crash occurrence without crashes actually having to occur to produce data. This is in contrast to the standard methods of safety analysis which are retroactive in nature, relying on long-term historic crash data to identify locations that are less safe than others for the purposes of prioritizing improvements.

Mousavi (2015) explains the methodology conducted in this research. Data collection was done through the use of GPS to generate naturalistic driving data. GPS units were placed in 31 study participants’ vehicles. The GPS data was filtered to remove erroneous data points. These errors include noise, wandering, and gaps in the GPS data. Noise was the most prevalent error and includes clusters of points around intersections where vehicles are moving slowly. Wandering occurred when GPS points appear in locations where no road exists and were seemingly random. Gaps were places along roadways where data points were missing due to loss of signal between the GPS units and satellites. These errors were removed with the use of the Savitzky‑Golay filter (Mousavi, 2015).

The next step in the methodology was differentiating the vehicles’ velocity values twice to obtain jerk values. Because data was collected at discrete time intervals, jerks were computed for each interval. Because the research in this thesis intended to conduct a microscale analysis, the roadways were segmented to obtain smaller study areas. Three different scales were tested: eighth-mile, quarter-mile, and half-mile segments. These segment lengths played a role in the calculation of road segment crash rates for each of the segments. This rate, expressed for 100 million vehicle-miles, was calculated using equation 17 from the US Department of Transportation, in which *C* is the number of crashes on a segment, *V* is the average daily traffic (ADT) on the segment, *N* is the number of years of crash data, and *L* is the road segment length (Mousavi, 2015).

 (17)

Input values for this equation were obtained to calculate the segment crash rates. Crash counts were obtained for a 5-year period between the beginning of 2009 and the end of 2013. There were 1,352 crashes on LA 1248 and 1,188 crashes on LA 42. The segment length varied between eighth-mile, quarter-mile, and half-mile segments depending upon the scale being tested. The ADT for each segment was computed by using data from the Louisiana Department of Transportation and the Inverse Distance Weighted interpolation tool within GIS software. With these input values, the crash rates could be calculated (Mousavi, 2015).

The thesis discusses a sensitivity analysis that was done to determine the proper jerk value to use as a threshold between normal and abnormal events. Because there is no clear threshold value to use for a continuous variable like jerk, a data-driven sensitivity analysis determined the best threshold value to use from a selection of test values. Threshold values tested began at -0.5 ft/s3 and decreased in increments of 0.5 ft/s3 until a final test threshold value of ‑10.5 ft/s3 was reached. A count of the number of abnormal events was then obtained and normalized based upon the total number of data points to obtain a jerk ratio for each of the segments. Again, three segment lengths were considered for both of the roadways included in the study. Pearson’s correlation coefficients were computed, and this analysis revealed that a jerk threshold of -2.5 ft/s3 and a segment length of one-quarter mile are most highly correlated with crash counts (Mousavi, 2015).

The next part of the analysis is crash frequency modeling. Two crash frequency models were created for each of the roads studied, thus resulting in four total models. The first type of model created includes only the jerk ratio as an independent variable. The second type of model includes both the jerk ratio and the presence of horizontal curvature as explanatory variables. Negative binomial regression was used to create all four models. Crash frequency modeling found that the jerk ratio was highly significant and possesses a positive correlation with crash rate. In contrast, the presence of curvature was only significant for one of the roads (LA 42) at a 95% level of significance. Therefore, presence of curvature may not be established as a meaningful predictor of crash occurrence. The value of the coefficient for the presence of curvature variable was computed to be negative, indicating that the presence of curvature tends to decrease the number of crashes that occur. This suggests that drivers adjust their behavior to drive more cautiously when curves are present, leading to fewer crashes (Mousavi, 2015).

The thesis concludes with a discussion of the limitations of the methodology and ideas for future research. Mousavi (2015) states that the GPS data was of low quality and low frequency. To capture braking information requires a high sampling rate. This problem may potentially be solved with the use of connected vehicle data. Additionally, the ADT values were interpolated using the Inverse Distance Weighted interpolation tool. This is a powerful tool, but it is possible that the interpolated values for ADT were not accurate. Having actual ADT counts would lead to a more accurate analysis. Mousavi (2015) calls for further research into the ideal segment length for jerk-cluster safety analysis with the use of a spatial analysis tool. Mousavi (2015) also suggests that detailed curve information, such as sharpness and radius, be included as explanatory variables in future safety models.

**Paper #9: “Assessing Surrogate Safety Measures using a Safety Pilot Model Deployment Dataset”**

This 2018 article was written by Zhaoxiang He, Xiao Qin, Pan Liu, and Md Abu Sayed and published in the journal *Transportation Research Record*. The article details a study in which SSMs were used in conjunction with data collected by the Safety Pilot Model Deployment (SPMD) program in Ann Arbor, Michigan. The SPMD program used connected vehicles and thirty items of roadside equipment to collect a variety of types of data on the vehicles involved in the program. He et al. (2018) used the kinematic data to evaluate the risk of mid-block rear-end crashes using SSMs.

He et al. (2018) used three different measures: TTC, modified TTC (MTTC), and DRAC. The difference between TTC and MTTC is the inclusion of acceleration in MTTC. TTC is based on the assumption of a constant vehicle speed, but MTTC allows for acceleration or deceleration to be considered. These measures were used as a safety index to determine the level of danger present on various links in Ann Arbor. The measures were then compared to actual crash data to determine the goodness of fit, using a statistical analysis with negative binomial regression. This statistical analysis reveals that the MTTC is the best of the SSMs (He et al., 2018).

He et al. (2018) include the equations they used to calculate the SSMs. These equations may be incorporated into other research that uses connected vehicle data. He et al. (2018) also present a map with the locations of crashes indicated as points and the safety index shown along links in the roadway network. Similar maps may be generated by other researchers using various GIS software programs such as ArcGIS. This could be a valuable addition to a study that investigates harsh braking events as SSMs.

He et al. (2018) end the paper with some suggestions for future research. One area in which researchers can build upon this study is in the data processing approach. He et al. (2018) acknowledge that their method of data processing may not be ideal due to some of the assumptions made. They call for research into finding other effective approaches as well as incorporating additional SSMs, such as PET and the difference in vehicle velocities. They also suggest that future research take place regarding the use of signal phasing and timing (SPaT) data. This research could potentially illuminate relationships between red light running and safety (He et al., 2018).

**Paper #10: “Surrogate Safety Measures from Traffic Simulation: Validation of Safety Indicators with Intersection Traffic Crash Data”**

The final paper considered, written by Vittorio Astarita, Ciro Caliendo, Vincenzo Pasquale Giofré, and Isidoro Russo and published in 2020 in the journal *Sustainability*, covers a study which proposes and validates a new SSM. This new measure uses vehicle trajectories and the mean energy of a vehicle to determine a safety metric and is capable of considering the dangers single vehicle crashes into roadside objects. These considerations have not been incorporated in SSMs prior to this paper. The researchers validate their new metric by comparing its results to both historical data and measures produced by other means, such as TTC and PET (Astarita et al., 2020).

Astarita et al. (2010) begin by reviewing the published literature on SSMs and highlighting concerns with the existing measures. They describe measures such as TTC, PET, and DRAC. They also describe a new traffic microsimulation program called TRITONE which evaluates road safety and has been validated through comparison with the SSAM. Astarita et al. (2010) list four topics which cause them concern with the existing measures: human factor modeling, traffic simulation packages, traffic safety indicators, and friction and shear forces in traffic flows.

The article goes on to describe the researchers’ reasoning behind each of the concerns. In terms of human factor modeling, the prior measures did not consider human error or human distraction. These are usually caused by drivers multitasking and account for approximately 30% of crashes in the United States. In considering traffic simulation packages, Astarita et al. (2020) raise concerns about the inability of most programs to compute SSMs as well as the SSAM’s inability to characterize crash severity or map locations of conflicts. In terms of traffic safety indicators, Astarita et al. (2020) point out that SSMs do not consider the outcome of a traffic conflict should it become a collision. Finally, Astarita et al. (2010) are concerned by the lack of consideration for potential conflicts between vehicles that are on trajectories that do not intersect or between vehicles and roadside objects.

With these concerns in mind, the researchers describe how their new SSM will address these lacunae. Beginning with a starting dataset for vehicle trajectories within a network, the researchers extract both the position and speed for every single vehicle in the dataset for every second of their simulation. For each of these vehicle speeds and locations, the researchers calculated deviated trajectories that are a particular angle to the right and to the left of the vehicle’s neutral trajectory along the road. The angle is generated with a Gaussian distribution. The deviated trajectories are then followed by the vehicle for a particular distraction time, which the researchers assumed to be five seconds. With these distracted paths calculated for the vehicles, potential collisions with other vehicles or roadside objects are determined, and the energy of impact in the crash is calculated using the physics of inelastic collisions (Astarita et al., 2020).

This methodology solves the concerns of the researchers in a number of ways. First, it takes human error and distraction into account through the deviated courses. This allows for conflicts between vehicles on paths that do not overlap to be considered, such as conflicts between vehicles traveling in opposite directions along a roadway. This also allows for single vehicle crashes to be represented as long as the location, shape, and material properties of roadside objects are included in the analysis. Finally, the crash dynamics are represented in the simulation, which means that impact energy is known. The researchers ran their simulation using TRITONE for four scenarios involving nine intersections in Salerno, Italy. The results of the simulations included numbers of crashes and mean collision energy. For comparison, the researchers also computed numbers of collisions from TTC and PET with threshold values (Astarita et al., 2020).

With these results, the article details a statistical analysis of the two methods of estimating crash counts. This analysis involves the computation of the root mean square error and likelihood ratio test statistic for each method. The researchers developed two models, Model A and Model B. Model A uses TTC, PET, traffic flow, and a dummy variable as explanatory variables. Model B uses mean collision energy, traffic flow, and a dummy variable as explanatory variables. The statistical analysis demonstrated that both of these models are statistically equivalent and Model B is able to estimate crash counts accurately as evidenced by a comparison to five-year crash counts. The findings of this paper suggest that crash counts may be successfully estimated using trajectory deviations to calculate mean collision energy and then fitting a model with that as an explanatory variable. Astarita et al. (2010) mention that their simulations made use of many default values for parameters, so they recommend further research into ways to calibrate this methodology to a specific area.

**Discussion**

Practitioners may apply the findings of the papers considered here to conduct a variety of types of surrogate safety analysis which vary in both the measures used and the way in which data is collected for the analysis. SSMs include time-based measures, deceleration-based measures, and safety indices. Time-based measures include TTC, TET, TIT, PET, IAPE, and PSD. Deceleration-based measures include DRAC and the use of harsh braking data as indicated by the jerk values experienced by vehicles. Safety indices include CPI and ACPM. The method used by Astarita et al. involved developing a crash prediction equation that uses a combination of time-based measures and traffic flow characteristics. Although it is possible to collect data for SSMs with in‑person observations or video data, the standard methods at this point in time include simulation with VISSIM or TRITONE models or use of connected vehicle data. Additional processing is necessary for both of these methods.

In order for practitioners to conduct surrogate safety analysis, they must first collect data on the intersection or link being considered. If using microsimulations, such data would include the roadway geometry and traffic characteristics. Analysis with simulation involves building models in VISSIM, TRITONE, or another suitable microsimulation program and then processing the output kinematic data with the Federal Highway Administration’s SSAM. The equations presented throughout this paper may also be used with such kinematic data to compute SSMs. Connected vehicle data is currently available through vendors but may eventually be available to the public in the future. Practitioners can use the kinematic data from connected vehicles as inputs to the SSM equations included throughout this paper as was done by He et al. Simulation and connected vehicle data allow for proactive safety analysis and preemptive safety improvements.

These papers vary in their levels of usefulness at this point in time. Newer papers, of course, have an advantage over older papers due to their authors having the benefit of a greater amount of prior research. However, some older papers, such as Allen et al.’s 1978 paper, still offer useful insights and SSMs. Table 1 is a rubric of the usefulness of the papers considered here with different categories that may concern practitioners looking into implementing their methods.

Table 1: Rubric of Usefulness for Papers Considered

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Paper Number - Year** | **Theoretical Value** | **Practical Value** | **Relevance** | **Difficulty of Implementation** |
| 1 – 1978  | Most | Most | Medium | Medium |
| 2 – 2001  | Medium | Medium | Medium | Medium |
| 3 – 2003  | Least | Most | Medium | Least Difficult |
| 4 – 2010 | Most | Least | Least | Most Difficult |
| 5 – 2011  | Least | Medium | Medium | Least Difficult |
| 6 – 2012 | Most | Least | Least | Most Difficult |
| 7 – 2013 | Most | Medium | Most | Medium |
| 8 – 2015 | Medium | Most | Most | Least Difficult |
| 9 – 2018 | Medium | Most | Most | Medium |
| 10 - 2020 | Most | Medium | Most | Most Difficult |

**Conclusions**

Traffic safety analysis with surrogate safety measures has evolved over the past several decades both in terms of the measures themselves and in the technology used to compute them. The articles and reports summarized in this paper range in publication year between 1978 and 2020, illustrating this evolution. The earliest method of computing surrogate safety measures was the use of time-lapse imagery which eventually gave way to microsimulation and, more recently, the implementation of connected vehicle data. Use of microsimulation greatly improved the precision with which surrogate safety measures may be computed but was also an abstraction. Connected vehicle data supplies both the realism of on-site measurement and the precision that is available with microsimulation, making it the preferred technology at this point in time. The measures have evolved from simply counting brake applications to taking kinematics into account or measuring rates of deceleration to determine where safety hazards exist. Surrogate safety measures are a means of preventing crashes and the damages, injuries, and loss of life that crashes cause. Research on surrogate safety measures has made great strides, as demonstrated by the articles considered in this paper. Continuing research into making these methods more easily implemented and more effective through the use of connected vehicle data could lead to much more effective safety analysis, more targeted infrastructure improvements, and safer roads and intersections for the public.

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