RU343

Bowtie Analysis without Expert Acquisition for Safety Effect Assessments of Cooperative Intelligent Transport Systems

Ute Christine Ehlers[1], Eirin Olaussen Ryeng, Dr.Eng.[2], Edward McCormack, Ph.D.[3], Faisal Khan, D.Sc.[4], Sören Ehlers, D.Sc.[5]

[1] PhD Candidate, Dept. of Civil and Environmental Engineering, NTNU Norwegian University of Science and Technology, 7491 Trondheim, Norway (corresponding author). Email: ute.ehlers@ntnu.no
[2] Associate Professor, Dept. of Civil and Environmental Engineering, NTNU Norwegian University of Science and Technology, 7491 Trondheim, Norway. Email: eirin.ryeng@ntnu.no
[3] Research Associate Professor and Director of the Master of Sustainable Transportation program, Dept. of Civil & Environmental Engineering, University of Washington, Seattle, W 988A 98195, USA. Email: edm@uw.edu
[4] Professor and Canada Research Chair of Offshore Safety and Risk Engineering, Faculty of Engineering and Applied Science, Memorial University, St. John’s, NL, A1B 3X5, Canada. Email: fikhan@mun.ca
[5] Professor and Head of the Institute for Ship Structural Design and Analysis, Hamburg University of Technology, 21073 Hamburg, Germany. Email: ehlers@tuhh.de

Abstract

Estimating the safety effects of emerging or future technology based on expert acquisitions is challenging, because the accumulated judgment is at risk to be biased and imprecise. Therefore, this semi-quantitative study is proposing and demonstrating an upgraded bowtie analysis for safety effect assessments that can be performed without the need for expert acquisition. While bowtie analysis is commonly used in the field of for example process engineering, it is novel in road traffic safety. Four crash case studies are completed using bowtie analysis while letting the input parameters sequentially vary over the entire range of possible expert opinions. The results suggest the following. Only proactive safety measures estimated to decrease the probability of specific crash risk factors to at least ‘very improbable’, are able to perceptibly decrease crash probability. Further, the success probability of a reactive measure must be at least ‘moderately probable’ to reduce the probability of a serious or fatal crash by half or more. This upgraded bowtie approach allows the identification of: (a) the sensitivity of the probability of crash occurrence and its associated consequences to expert judgment used inside the bowtie model, and (b) the necessary safety effectiveness of a chosen safety measure allowing adequate changes in the probability of crash occurrence and its consequences.

Keywords: Bowtie; Fuzzy sets; Expert judgment; Safety effect; Cooperative intelligent transport systems

Introduction

Cooperative intelligent transport systems (C-ITS) are an emerging technology in the field of automotive and transportation engineering, and expectations are high that their application will positively influence road traffic safety, among other transport related issues. As with any other new or future technology, it is challenging to reliably estimate the effects and impacts this technology might have. Facing this uncertainty concerning the future, and involving a lack of knowledge, research is often based on expert judgment. Unfortunately, this form of data, its elicitation as well as interpretation, has been found to be prone to a large number of biases for various reasons (e.g. Eddy 1982; Meyer and Booker 1991; Tetlock 2005; Kirkebøen 2009; Kahneman 2011; Lees 2012; Morgan 2014). For instance, Kassin et al. (2013) provided a comprehensive overview of recent research indicating the not uncommon existence of confirmation bias among experts in various disciplines of forensic science. Confirmation bias is a psychological phenomenon “by which people tend to seek, perceive, interpret, and create new evidence in ways that verify their preexisting beliefs” (Kassin et al. 2013). In the context of expert judgment in traffic safety, additional types of bias can be problematic, e.g. hindsight bias and publication bias (Shinar 2017). Hindsight bias, also called knew-it-all-along effect, is the tendency of people to increase the perceived likelihood of an event or its outcome after the event has in fact occurred. This bias embodies “beliefs about events’ objective likelihoods, or subjective beliefs about one’s own prediction abilities” (Roese and Vohs 2012), and thus can be problematic in the reconstruction and causation analysis of crashes (Dilich et al. 2006). Publication bias is the tendency to not publish ‘negative’ results which seems likely to also have an impact on the judgment of experts. Overviews on bias-reducing strategies and techniques that aim for high accuracy in expert judgment are provided in a number of publications, e.g. Meyer and Booker (1991), Kirkebøen (2009), or Morgan (2014). For example, the use of explicit decision rules like the Bayes theorem and the training for it, or incorporating specific group decision processes, have been shown to reduce bias (e.g. Meyer and Booker 1991; Rowe and Wright 2001; Surowiecki 2004). Plus, in the absence of empirical data, the use of data accumulated in expert acquisitions seems to be the only data on which research can possibly be based on. However, not even the best expert could exactly forecast the future performance of a specific novel system, its effects, and their likelihood.

Another challenge evolves when estimating the actual safety effects of cooperative intelligent transport systems (C-ITS) in terms of their influence on crashes. Apart from the possibility to implement various C-ITS with different levels of maturity in many different ways, long periods of exposure to real traffic are necessary to collect a significant level of crash data. The majority of C-ITS are still in their test phase. Even applications, whose deployment has already been started to a limited extend, are far from providing enough real traffic and crash data in order to be able to estimate safety effects in a statistically reliable manner. Further, a substantial portion of vehicles will have to be equipped with C-ITS before the anticipated and actual safety effect would show. Due to this current lack of empirical data, research has been based on “by proxy” or surrogate methods to assess the effects of safety-related C-ITS that are not yet implemented in real traffic, or have been implemented for a relatively short time. “By proxy” or surrogate methods can be in-depth analyses of crash reports (Virtanen et al. 2006), ex-ante estimate studies based on e.g. crash data and statistics (Wilmink et al. 2008; Schirokoff et al. 2012), traffic simulation modelling, driving simulator and field test studies, or a combination of those (Harding et al. 2014). Ex-ante estimate studies are based on in-depth investigations of crashes, and analyze whether crashes or fatalities could have possibly been prevented if a specific safety measure would have been used (e.g. Vaa et al. 2014). These studies usually involve numerous assumptions regarding vehicle fleet penetration rates and infrastructure coverage, future trends, anticipated driver behavior, and the functional and technological features of the system under research. Hardly any of the found surrogate evaluation methods allows a practical and fast safety effect estimation of new or future C-ITS while allowing for the various factors that are associated with crash occurrence and its consequences. Moreover, surrogate methods have one important disadvantage. Crash risk is not measured directly. Instead, road safety is measured indirectly through performance indicators, such as speed or driver behavior. Although their relation or even correlation to crashes and their consequences is known to some extent, the true effects of ITS on driver behavior particularly are still unsolved – especially the long term effects.

Ehlers et al. (2017) proposed bowtie analysis (BTA) as a probabilistic risk assessment method to the field of road traffic safety to allow the estimation of the safety effects of C-ITS before their introduction or wide deployment. The authors consider bowtie analysis a valuable method to systematically and quantitatively assess the effects of safety measures, such as safety-related C-ITS. In detail, bowtie analysis showed to be applicable when assessing the change in the probability of both crash occurrence and the related consequences, due to the use of proactive or reactive safety measures. Proactive safety measures are hereby understood as measures that intend to reduce the probability of crash occurrence, while reactive safety measures are supposed to reduce the probability of severe crash consequences. The proposed bowtie analysis was based on exemplary expert estimates, which was created and applied solely for demonstration purposes. In detail, those expert estimations were generated for the occurrence and success probability of specific events as fuzzy sets using linguistic terms, such as ‘highly improbable’ or ‘moderately probable’.

This study is an extension of the study by Ehlers et al. (2017) and attempts to demonstrate an upgraded bowtie analysis, by eliminating its dependency on expert acquisitions, and thereby subjective expert opinions. Instead of involving experts, bowtie analysis is conducted for four cases by letting the input parameters sequentially vary over the entire range of possible expert opinions. The results of these four case studies are then compared to a base case, whose input parameters should ideally be based on existing knowledge and empirical evidence, such as crash statistics, in-depth and meta-analyses. This allows the identification of (a) the sensitivity of the probability of crash occurrence and its associated consequences to expert judgment; and (b) the necessary safety effectiveness of a C-ITS allowing for adequate changes in the probability of crash occurrence as well as its consequences. Thereby, a method is created that aims to support public decision makers such as road authorities to identify *the minimum safety effectiveness* required for emerging C-ITS or other future safety measures without the need for conducting expert acquisitions.

C-ITS are created by placing information and communication technologies at the roadside and inside vehicles in order to collect, process, transfer and deploy traffic- and safety-related data. Wireless short range radio communication between the road infrastructure, vehicles and personal electronic devices allows a utilization of the following interactions: vehicle-to-vehicle communication (V2V), and vehicle-to-infrastructure communication (V2I). These information and communication links can be one-way or two-way. Cooperative vehicles (V2V) would be able “to see” one another through wireless high-speed, real-time communication, and would receive relevant data, such as position, speed, course and type of the other vehicles. Compared to non-cooperative vehicles and transport systems, the information and warning timing would be improved. System users would be able to receive information and warnings in real time, enhancing the situation awareness of the drivers, providing them with additional reaction time. In addition, V2V-systems could augment existing sensor-based intelligent transport systems, thereby improving accuracy, and support vehicle control (OECD 2003; Bayly et al. 2007; Harding et al. 2014).

The focus of this study is on C-ITS that are expected to directly improve road traffic safety by reducing the probability of crashes and their consequences, hereafter called safety-related C-ITS. Examples of (potential) safety-related C-ITS applications include intelligent speed adaptation, emergency call systems, and various incident detection and warning systems such as local danger warning, red light violation warning or curve speed warning, and many more. The ‘road traffic safety problem’, i.e. the number of injuries and fatalities resulting from crashes, can be understood as a function of the three variables exposure, crash risk and injury consequence; see Equation 1 (Nilsson 2004). In this equation, the word ‘accident’ is synonymous with ‘crash’.

$$Number\ of\ injured = Exposure \times \overbrace{\left(\frac{Number\ of\ accidents}{Exposure}\right)}^{\text{Risk}} \times \overbrace{\left(\frac{Number\ of\ injured}{Number\ of\ accidents}\right)}^{\text{Consequence}} \qquad (1)$$

Exposure to the risk of traffic accidents is for example expressed in person or vehicle kilometers travelled. Accident rate is understood as the risk of a traffic accident per unit of exposure, thus often referred to as accident risk. The above mentioned concept of risk in road traffic safety should not be confused with the traditional definition of risk = probability * consequence, which is usually used in risk assessment and therefore further in this article.

After this introduction, the background of this study will be covered with a short review of the theories behind bowtie analysis and fuzzy set theory. Crash scenarios, the base case and additional assumptions taken from former research will be described as well. The next part will provide the framework used in this study. The case studies will be carried out subsequently. Finally, the results of all bowtie analyses and their implication will be discussed; and the conclusions of this study will be presented.

Background

Bowtie analysis and fuzzy set theory

Bowtie analysis (BTA) is a method just recently proposed to the field of road traffic safety (Ehlers et al. 2017), but commonly used in probabilistic risk assessment to qualitatively and quantitatively identify causes and consequences of a risk or hazardous event (Dianous and Fiévez 2006; Duijm 2009; IEC/ISO 31010 2009; Jacinto and Silva 2010; Ferdous et al. 2012, 2013). It combines the two well-established risk assessment techniques fault tree analysis and event tree analysis, but also includes safety barrier, or safety measure elements. The focus of this method also lies on the effectiveness evaluation of both proactive and reactive safety measures used to reduce or prevent the risk, or to mitigate its consequences.

More specifically, a bowtie model and its diagram consist of the following events and safety measures. They are also applied in this study:

a) Causal (root) factors, called *basic events* (BE), initiating or contributing to the malfunction of the system

b) Malfunctions, errors or other faults and causes, called *intermediate events* (IE), causing the undesired critical event

c) Proactive countermeasures implemented, or planned to be implemented, here called *proactive safety measures* (PSM)

d) The *critical event* (CE)

e) Reactive countermeasures implemented, or planned to be implemented, here called *reactive safety measures* (RSM)

f) Consequences of the critical event, called *outcome events* (OE)

In the quantitative BTA, the occurrence probability of the basic events and intermediate events is acting as quantitative input together with the success probability of the safety measures. The occurrence probability of the critical event as well as outcome events represents the quantitative output and result of the analysis. In an ideal world, all input data would be known with high accuracy. In real life however, lacking or limited input data necessitates the assignment of expert judgment, which tends to be subjective and possibly imprecise. Ferdous et al. (2012) presented a framework for handling both types of uncertainty in BTA by means of fuzzy set theory which is adapted and applied in this study.

The application of *fuzzy set theory* has been proven to be efficient when handling subjective, imprecise information and non-crisp data such as lingual expert judgment (e.g. Zadeh 1965; Bouchon-Meunier et al. 1999; Ayyub and Klir 2006; Markowski et al. 2009; Ferdous et al. 2012). For example, experts may use the following *term set for probability* to estimate the occurrence probability of events and the success probability of safety measures, as in this study: *highly improbable* (HI), *very improbable* (VI), *improbable* (I), *moderately probable* (MP), *probable* (P), *very probable* (VP) or *highly probable* (HP). Such linguistic terms can then be converted to fuzzy numbers, for example *triangular fuzzy numbers* (TFN)$x \in P$, to represent the membership functions (for further details, please see Bouchon-Meunier et al. 1999; or Ayyub and Klir 2006). These describe in what degree a number belongs to a set by using a numerical relationship, see Fig. 1. Each fuzzy number *P* is then described as a vector $\mathbf{p_L}$, $\mathbf{p_m}$, $\mathbf{p_U}$ that is represented by the lower boundary, the most likely value (i.e. at the mode) and the upper boundary of the TFN *P*. Multiple and possibly inconsistent expert knowledge can be aggregated by applying the *weighted average method* (e.g. Ayyub and Klir 2006). After the input variables are assigned with the probabilities using TFNs, fuzzy arithmetic operations can be used to perform the bowtie analysis (Ferdous et al. 2012). These fuzzy arithmetic operations and equations are based on the traditional equations from fault and event tree analysis, see e.g. IEC 61025 (2006) and IEC 62502 (2010).

Crash occurrence assumptions and crash scenarios

Although crashes are rare and random in their occurrence, in this study the crash is assumed to occur, i.e. the crash occurrence probability is close to one. This approach, with one specific crash and its 'causal chain', is chosen because of the illustrative and demonstrative purpose of this study, and should not be confused with the actual probability or frequency of a specific crash type, which would have to be based on crash data.

Ehlers et al. (2017) chose three illustrative crash scenarios, which are also used in the case studies hereafter. The following assumptions, valid for all three crash scenarios, were made for the crash assumed to occur at an example road section. The critical event was defined as the occurrence of a run-off-road collision of a single passenger car. More specifically, a single passenger car with one vehicle occupant is leaving the roadway at a section, where a rock cut is located at the roadside. The speed limit of this road section is 80 km/h. It is presumed that the vehicle occupant, i.e. the driver, wears a seat belt, and that the vehicle collides with a guardrail meant to shield the rock cut beside the road. The case studies were based on three different applications of safety measures, which can be distinguished as proactive or reactive in relation to the crash occurrence, see Fig. 2. The first crash scenario was understood as the baseline scenario, where two traditional safety measures, are applied. The other two crash scenarios have been an extension of the baseline scenario, applying either a proactive or reactive cooperative safety measure in addition to the traditional ones. Several basic and intermediate events, listed in Table 1, were chosen as parameters with the potential to initiate and cause the crash. That means at least one basic event has been assumed to initiate the crash, possibly in combination with at least one other basic event. The outcome events were defined using different levels of injury severity, following a classification according to the Maximum Abbreviated Injury Scale (MAIS 1-6). For example, MAIS 1 has been defined a minor injury that requires a short term medical treatment, such as stiches, while MAIS 6 has been defined representing a fatal injury.

The base case and its bowtie analysis (BTA1)

Ehlers et al. (2017) performed bowtie analyses for five case studies. The initial case study, thus initial bowtie analysis (BTA1), should be understood as the base case to which the results of this study are compared to.

The base case was based on crash scenario 1, i.e. the baseline scenario, where the two traditional and non-cooperative safety measures seat belt and guardrail are applied. Fig. 3 shows the bowtie diagram that was developed for the base case and its bowtie analysis (BTA1). The proactive safety measure (PSM) is additionally applied later on in BTA2, and is not part of BTA1. A short description of the input and output events of BTA1 is given in Table 2. The crash outcomes, thus resulting injury severities, were chosen based on the crash scenario and its underlying assumptions. It was assumed the driver sustains injuries in each crash outcome, due to the sudden and significant change in velocity, given the speed limit of 80 km/h.

The probabilities of the input events for the quantitative bowtie analysis should ideally be based on existing knowledge and empirical data. For example, the success probability of the reactive safety measures seat belt and guardrail was chosen from a literature source (Elvik et al. 2009) as fuzzy numbers: the probability of success of the driver's seat belt in a passenger car is (0.230, 0.280, 0.330); and the one of a guardrail is (0.365, 0.455, 0.530). However, it is important to note that the occurrence probabilities of the basic events were generated as example expert data, due to the purpose to demonstrate bowtie. In future research, it should be possible to use the actual approximate occurrence probability of the most representative basic events through crash statistics, under the thorough consideration of the crash type, in-depth crash study results and more. Ideally, the probabilities of the basic events would be chosen from an existing crash causation assessment study. Table 3 shows the generated occurrence probabilities and the chosen success probabilities of the input events in fuzzy scale.

Based on these input probabilities, the fuzzy based probabilities of the critical event (CE) and the different crash outcome events (OE) were calculated using fuzzy arithmetic operations for bowtie analysis, see Table 4. The calculated probability of the critical event was (0.839-0.998). Further, a crash with a critical or fatal injury (MAIS 5-6), was the most likely outcome calculated. This is because a combined failure of the two traditional safety measures seat belt and guardrail, whose success probability is judged to be relatively high, would have serious consequences. Success of a safety measure means thereby that the safety measure in question fulfills its tasks and performs as planned, under the assumption that it is provided and used as intended. The probability of the other crash outcomes was found to decrease with decreasing injury severity.

Framework used in this study

In this study, a framework adapted from Ferdous et al. (2012) and Ehlers et al. (2017) is applied to perform bowtie analysis, covering the full range of expert opinions on event probability, as conceptual approach for evaluating the safety effects of C-ITS, see Fig. 4. The quantitative bowtie analysis includes a fuzzy based approach with the following steps in the following order:

1. Generation of full-range expert opinion in form of linguistic terms, covering the whole range of possible event probability (e.g. from ‘highly improbable’ to ‘highly probable’) to define the changed probability of the input events due to the application of a new safety measure
2. Transformation of linguistic terms into triangular fuzzy numbers
3. Aggregation of fuzzy numbers in case of opinions from multiple experts
4. Determination of the probability of the critical event and outcome events by applying the modified fuzzy arithmetic operations

Probability assessments based on bowtie analysis using expert knowledge usually provide an approximate quantification of the occurrence likelihood of a critical event and its outcome events without considering the whole spectrum of possible expert judgments. For example, if another expert holds an oppositional belief compared to the expert judgment acquired before, the judgment of all experts would be aggregated and averaged by applying for example the weighted average method. Furthermore, although a fuzzy based approach allows the handling of subjective and imprecise expert judgment to a certain extent, it cannot cover all parameter uncertainty of these types in the estimated input data. Therefore, this study uses a systematic approach, where the parameters of the input data is simulated to sequentially vary over the entire range of possible event probability – i.e. from ‘highly improbable’ to ‘highly probable’ in linguistic terms. Thereby the effect of changing input parameters on the analysis results can be studied and evaluated. In detail, this approach provides the lower and upper boundaries within which the occurrence probability of the crash and its outcome events (i.e. consequences) may lie, when the parameters of the input events vary over the entire range of probability.

Case study 2 (BTA2) and 3 (BTA3): simulated variation of expert judgement on the occurrence probability of the basic events (fault tree)

While the input data of the base case should ideally be, and is already partially based on empirical knowledge, the additional four case studies are based on full-range expert opinions. This means, instead of using a specific, thus limited spectrum of expert judgment, the probability of all input events is simulated to sequentially vary from ‘highly improbable’ to ‘highly probable’. This means, no data from expert acquisitions is used in this study. Finally, the probability of the output events in the initial base case can be compared to the one in the other study cases, which allows a safety effect assessment of the new safety measures applied in addition to the traditional ones.

In case study 2 (BTA2), a cooperative proactive safety measure is applied in addition to the two traditional ones, as visualized in the crash scenario 2. A local danger warning system is chosen as proactive C-ITS as an example. Its application is assumed to positively influence the occurrence probability of six of the 18 basic events: three driver-related and three road-related, see Fig. 3. The occurrence probability of the other 12 basic events remains unchanged. A short description of the input and output events of this crash scenario is provided in Table 5. Theoretically, experts could be asked the following question in order to acquire their opinions on the effect of the chosen C-ITS on the occurrence probability of the six basic events: “*Given a successful* *application of the stated proactive safety measure, how probable (likely) is it that this specific basic event, possibly in combination with other basic events, still occurs and initiates the crash?"* But instead of involving experts, the occurrence probability of the six basic events is now assigned with lingual terms that cover the whole range of probability from 'highly improbable' to 'highly probable'. Thereby, the probability of the six basic events varies simultaneously. The occurrence probability of the other basic events and the success probability of the reactive safety measures remain the same as in the base case (BTA1).

Fig. 5 visualizes the results of BTA2. The vertical lines in the following figures represent the triangular fuzzy numbers (TFN) of the likelihoods of occurrence of the regarding event. The upper end of each vertical line represents the upper boundary value of the TFN (i.e. the right value of the TFN), while the lower end of the line represents the lower boundary value (i.e. the left value of the TFN). The actual data point, between the lower and upper boundary value, is the most likely value (i.e. the modal value of the TFN) of the occurrence likelihood of the event under analysis. The dotted horizontal lines represent the probabilities of the critical event (CE) and outcome events (OEs) of *the base case* in BTA1, with which the new probabilities of BTA2 are compared. The results show that the occurrence probability of all output events starts to decrease, when the occurrence probability of the six basic events in question is estimated to be at least 'improbable'. Further, the application of a proactive safety measure, that is estimated to increase the occurrence probability of the six basic events *compared to the base case*, tends to slightly increase the likelihood of a crash as well as its outcome events.

In case study 3 (BTA3), variable linguistic terms are assigned to the occurrence probability of *all basic events*. Thereby, the occurrence probability of all basic events is simulated to vary simultaneously from 'highly improbable' to 'highly probable'. This is supposed to simulate a full-range expert opinion on the effect of a cooperative proactive safety measure on the occurrence probability of all basic events. In addition, the effect of a varying occurrence probability of the basic events on the quantitative bowtie analysis results can be studied. Again, the success probability of the two traditional reactive safety measures, seat belt and guardrail, remains the same as in the base case (BTA1). Fig. 6 visualizes the results of BTA3, which also reflect the results of BTA2. The occurrence probability of the critical event becomes 1, when the occurrence probability of all basic events is estimated as at least moderately probable. The results show that the likelihood of a crash and its related outcome events decreases together with the occurrence probability of the basic events. Further, a crash is almost unavoidable, even if the occurrence probability of all basic events would be estimated as *very improbable*. Only if the occurrence of *all basic events* would be estimated as *highly improbable*, the crash probability could be reduced by more than half. The reason for this lies in the assumption made for the bowtie analyses: it is assumed that at least one factor will occur that will initiate or contribute to a malfunction of the system leading to a crash. For example, the occurrence probability of the crash would be close to 1, even if the occurrence probability of *all basic events, except for one*, would be estimated being highly improbable – given that the occurrence probability of *this one basic event* would be estimated as highly probable. Again, the probability of crash occurrence would decrease with a decreasing probability of that one basic event.

An additional effect is found regarding the amount of basic events, thus crash risk factors. If their number would be reduced, the calculated likelihood of crash occurrence would also reduce, which reflects the arithmetic in the bowtie model.

Case study 4 (BTA4) and 5 (BTA5): simulated variation of expert judgment on the success probability of the reactive safety measures (event tree)

In case study 4 (BTA4), variable linguistic terms are assigned to the success probability of the *two traditional reactive safety measures* seat belt and guardrail. Though the actual success probability of these measures is known and taken from a credible literature source (Elvik et al. 2009), its effect on the output data while letting it vary is of interest. The occurrence probability of all basic events remains the same as in the base case (BTA1), and so does the bowtie diagram. The results show that, if highly ineffective reactive safety measures are applied, a crash with 'a critical or fatal injury' (OE4) would be extremely likely, see Fig. 7. In contrast, if highly effective safety measures are applied, the outcome would tend to be 'a minor to serious injury' (OE1). This means, the application of highly ineffective reactive safety measures would tend to worsen the outcome and vice versa. The occurrence probability of a crash with a minor to serious injury as outcome increases with a decreasing occurrence probability of a crash with a critical or fatal injury as outcome. If the success probability of all reactive safety measures is estimated to be moderately probable, the occurrence probability is calculated to be the same for all outcome events.

In case study 5 (BTA5), the varying linguistic terms are only assigned to the estimated success probability of the *cooperative reactive safety measure* that is additionally applied as illustrated in crash scenario 3. These linguistic terms would be assumed to be given as expert opinions when asking the following question: *"Given a crash under the defined settings, how probable (likely) is a success of the applied novel reactive safety measure?"* Again, the expert opinion is simulated to vary over the entire range of success probability. The emergency call system eCall is chosen as cooperative reactive measure that automatically calls and notifies the nearest emergency center, right after the vehicle sensors have detected the crash. Saving emergency response time, thus possibly lives, is expected from equipping all new cars with the eCall technology (EC 2016). The probability of the other input events remains the same as in BTA1. Fig. 8 illustrates the event tree for BTA5 applying the cooperative eCall system as additional reactive safety measure. Table 6 lists all the events and measures that are involved. It is assumed that the eCall system is neither affecting the least, nor the worst crash outcome.

Fig. 9 illustrates the results of BTA5 compared to the base case in BTA1. Fig. 10 displays the results for the outcome events OE2 to OE5 in detail. The occurrence probabilities of BTA1 are again plotted as horizontal dotted lines. The sum of the probabilities of OE2 and OE3 is equivalent to the probability of OE2 in the base case ($OE2_{base}$); see Fig. 10(a). This is because of the formulae used in the event tree analysis (i.e. right side of the bowtie diagram), and because the least and worst outcome are assumed to be not affected by the application of the eCall system. The same occurs for the sum of OE4 and OE5, being equivalent to the probability of OE3 in the base case ($OE3_{base}$); see Fig. 10(b). The occurrence probability of the CE remains unchanged. The same applies for the occurrence probability of the least outcome OE1 (i.e. minor to serious injury crash with MAIS 1-3), and worst outcome OE6 (i.e. critical or fatal injury crash with MAIS 5-6). Thereby OE6 represents the former OE4 from the base case ($OE4_{base}$). However, the probability of the other outcomes changes depending on the estimated success probability of the eCall. Both, the probability of a serious to critical injury crash (i.e. OE3, former $OE2_{base}$) and the probability of a severe to fatal injury crash (i.e. OE5, former $OE3_{base}$), is decreasing with increasing success likelihood of the additional safety measure. The success probability of the eCall system needs to be judged as at least ‘moderately probable’ in order to reduce the probability of a serious to critical injury crash, as well as the probability of a severe to fatal injury crash, by half or more compared to the base case.

Discussion

There is a need for methods that allow assessing *the direct safety effects* of emerging or future cooperative intelligent transport systems (C-ITS) to be applied in the field of automotive or transportation engineering. Ehlers et al. (2017) proposed bowtie analysis as safety effect assessment tool to be used in the field of road traffic safety. Performing bowtie analysis with simulated varying expert judgment as proposed and demonstrated in this paper is upgrading the bowtie analysis approach. It allows estimating the safety effect of a specific safety measure, independently of expert judgment on the safety measure’s effectiveness. In other words, this upgraded approach simulates the entire range of possible expert answers (i.e. probabilities) by altering the input data that usually comes from expert acquisitions, which are at risk for several types of bias and uncertainties. Fig. 11 provides a flowchart of the proposed bowtie approach.

Under the assumptions made for this study, the results of the second and third bowtie analysis (i.e. simulated variation of expert opinion on the occurrence probability of the basic events) suggest the following. Only *proactive C-ITS* that are estimated to decrease the occurrence probability of the specific crash risk factors (i.e. the ones that are representative for the crash type in question) to at least ‘very improbable’, are able to perceptibly decrease the occurrence probability of a crash. Otherwise, the crash would be highly likely. Obviously, an ideal proactive C-ITS would be able to decrease the occurrence probability of *all* basic events, thus crash risk factors, down to ‘highly improbable’. That means, the occurrence of a crash would very likely be prevented, given: (a) the application of a proactive safety measure that is able to timely inform and warn the driver about *all* potential driving errors, vehicle or infrastructure malfunctions and environmental anomalies, and (b) a prompt and adequate reaction of the driver according to the received warning.

Regarding the bowtie model, its arithmetic yields a decrease in the calculated likelihood of crash occurrence with a decreasing number of basic events. This may suggest a careful deliberation, whether basic events, whose occurrence is highly improbable, need to be included in the final fault tree model, or not. When two similar proactive C-ITS are to be compared, the following applies. The more basic events are positively influenced, the better. This means, the system able to decrease the occurrence probability of the basic events qualitatively and quantitatively the most can be assumed to have the bigger safety effect.

The results of the fourth and fifth bowtie analysis (i.e. simulated variation of expert opinion on the success probability of the reactive safety measure) indicate the following. Under the assumptions made for this study, the probability of a serious to critical injury crash, and the probability of a severe to fatal injury crash can be reduced by half or more, if the success probability of the chosen *reactive C-ITS* eCall is estimated at least 'moderately probable'. In fact, it is the application of any additional reactive safety measure that positively affects the crash outcomes, because its application yields an even more fragmented classification of the injury severity – given that it works as successful as assumed in the qualitative consequence analysis.

Bowtie analysis holds a limitation that is apparent when applied to the field of transportation safety. That is the assumption of statistical independency between the input factors. In real life, interdependencies and correlations between crash risk factors are evident. Further, crash risk factors are known to have an influence on the crash outcome. In bowtie analysis, the probability of the risk factors (i.e. basic events) is only considered in the calculation of the critical event probability, but not in the calculation of the outcome events. Moreover, direct effects of emerging technologies on driver behavior are still unsolved and thus involve a high grade of uncertainty. For these reasons, bowtie analysis may be criticized to oversimplify the dynamic and complex behavior of crash occurrence, including its consequences. However, models are typically created and applied to simplify reality in order to allow problem solving which naturally includes model uncertainty. Other limitations and uncertainties may concern the data used in the bowtie model for safety effect estimation purposes. These may involve variations and incomplete information in the empirical crash data. Evidently, an increase in the accuracy of the input data will strongly improve the quality of the model output, i.e. safety effect estimations. Bayesian analyses are one way to model these uncertainties. Through automatized big data collection, it might be possible to precisely quantify the occurrence probability of all crash risk factors in the future, while taking into account their interrelations and variations. Bowtie analysis and its developments are applicable also for this purpose, as it allows for dynamic updates of the input parameters given new evidence (e.g. Ferdous et al. 2012; Paltrinieri et al. 2013). Overall, crash models can be expected to become more accurate, and shall then also allow the modelling of dynamic processes and interdependencies – including human behavior factors.

Conclusion

This paper demonstrated the application of an upgraded bowtie approach in a semi-quantitative assessment of emerging safety measures potentially used in the field of transportation. Four case studies were completed using bowtie analyses, whose input parameters sequentially varied over the entire range of possible expert answers. These results were compared with the results of an initial base case study, whose input data was partially generated as example, and partially based on existing knowledge. This allowed the identification of: (a) the sensitivity of the probability of crash occurrence and its associated consequences (i.e. output data) to the whole spectrum of expert judgment used inside the bowtie model, and (b) the necessary safety effectiveness of a chosen C-ITS allowing adequate changes in the probability of crash occurrence and its consequences.

Whereas the bowtie approach holds the limitation of assuming independency between the input parameters, it allows for a practical assessment of C-ITS and their safety effects necessary to achieve adequate changes in the occurrence probability of crashes and their associated consequences. By using this method, decision makers such as road authorities can identify *the minimum safety effectiveness* necessary to be achieved by C-ITS or other future safety measures, and choose the best investments to support safety. The upgraded bowtie approach demonstrated in this study allows for assessments without expert data acquisitions, which usually are at risk for uncertainty and bias. Yet, a purposeful communication and interpretation of the potential safety effects of these measures is made possible. Future research may address the limitations of bowtie analysis such as the assumed independency among input events. For example, the introduction of a dependency coefficient could explore different kinds of interdependence. An additional sensitivity analysis could determine the most significant contributing input events for the output events. This may support the final selection of the basic events for the bowtie model.

Acknowledgments

The authors gratefully acknowledge the financial support provided by the Norwegian Public Roads Administration.

References

Ayyub, B. M., and Klir, G. J. (2006). *Uncertainty Modeling and Analysis in Engineering and the Sciences*. Chapman & Hall/CRC.

Bayly, M., Fildes, B., Regan, M., and Young, K. (2007). Review of Crash Effectiveness of Intelligent Transport Systems. TRACE.

Bouchon-Meunier, B., Dubois, D., Godo, L. and Prade, H. (1999). Fuzzy sets and possibility theory in approximate and plausible reasoning. In Bezdek, J., Dubois, D. and Prade, H. (Eds.), *The Handbook of Fuzzy Sets*, vol. 5. Kluwer Academic Publishers, 15-190.

Dianous, V., and Fiévez, C. (2006). "ARAMIS project: A more explicit demonstration of risk control through the use of bow-tie diagrams and the evaluation of safety barrier performance." *J. Hazard. Mater.*, 130, 220-233.

Dilich, M., Kopernik, D., and Goebelbecker, J. (2006). "Hindsight judgment of driver fault in traffic accident analysis: Misusing the science of accident reconstruction." *Transportation Research Record: Journal of the Transportation Research Board*, Volume 1980, 1-7.

DRIVE (Dedicated Road Infrastructure for Vehicle Safety in Europe) (1989). R&D in Dedicated Road Infrastructure for Vehicle Safety in Europe (DRIVE): Progress Report '89 and Mid-term Review. Communication from the Commission to the Council and the European Parliament. SEC (89) 1990 Final. DRIVE, Brussels.

Duijm, N. J. (2009). "Safety barrier diagrams as a safety management tool." *Reliab. Eng. Syst. Saf. 94*, 332-341.

Eddy, D. (1982). Probabilistic reasoning in clinical medicine: Problems and opportunities. In Kahneman, D., Slovic, P., Tversky, A. (Eds.). *Judment under uncertainty: Heuristics and biases.* 249-267. Cambridge University Press, Cambridge, England.

Ehlers, U. C., Ryeng, E. O., McCormack, E., Khan, F., and Ehlers, S. (2017). "Assessing the safety effects of cooperative intelligent transport systems: A bowtie analysis approach." *Accid. Anal. Prev.*, 99 (2017), 125-141.

Elvik, R., Høye, A., Vaa, T., and Sørenson, M. (2009). *The Handbook of Road Safety Measures*, 2nd edition. Emerald, Inc.

EC (European Commission) (2016). "eCall: Time saved = lives saved". Digital single market. ‹https://ec.europa.eu/digital-single-market/ecall-time-saved-lives-saved› (Feb. 1, 2017)

Ferdous, R., Khan, F., Sadiq, R., Amyotte, P., and Veitch, B. (2012). "Handling and updating uncertain information in bow-tie analysis." *J. Loss Prev. Process Ind.*, 25, 8-12.

Ferdous, R., Khan, F., Sadiq, R., Amyotte, P., and Veitch, B. (2013). "Analyzing system safety and risks under uncertainty using a bow-tie diagram: an innovative approach." *Process Saf. Environ. Prot.*, 91, 1-18.

Harding, J., Powell, G., Yoon, R., Fikentscher, J., Doyle, C., Sade, D., Lukuc, M., Simons, J., and Wang, J. (2014). Vehicle-To-Vehicle Communications: Readiness of V2V Technology for Application. National Highway Traffic Safety Administration. U.S. Department of Transportation, Washington D.C. (Report No. DOT HS 812 014).

IEC 61025 (2006). "Fault Tree Analysis (FTA)". International Electrotechnical Commission.

IEC 62502 (2010). "Analysis Techniques for Dependability - Event Tree Analysis (ETA)". International Electrotechnical Commission.

IEC/ISO 31010 (2009). "International Standard: Risk Management - Risk Assessment Techniques". International Electrotechnical Commission.

Jacinto, C., and Silva, C. (2010). "A semi-quantitative assessment of occupational risks using bow-tie representation." *Safety Science*, 48 (2010), 973-979.

Kahneman, D. (2011). *Thinking Fast and Slow*. Farrar, Straus and Giroux, New York.

Kassin, S. M., Dror, I. E., and Kukucka, J. (2013). "The forensic confirmation bias: Problems, perspectives, and proposed solutions." *Journal of Applied Research in Memory and Congnition*, 2, 42-52.

Kirkebøen, G. (2009). Decision behaviour – Improving expert judgement. In Williams, T. M., Samset, K., Sunnevåg, K. J. (Eds.). *Making Essential Choices with Scant Information: Front-End Decision Making in Major Projects*. Palgrave Macmillan, 169-194.

Lees, F. P. (2012). *Lees' Loss Prevention in the Process Industries: Hazard Identification, Assessment and Control*, 4th edition. Elsevier.

Markowski, A. S., Mannan, M. S., and Bigoszewska, A. (2009). "Fuzzy logic for process safety analysis." *J. Loss Prev. Process Ind.*, 22, 695-702.

Meyer, M. A., and Booker, J. M. (1991). *Eliciting and Analyzing Expert Judgment: A Practical Guide*. Academic Press Limited, London.

Morgan, M. G. (2014). "Use (and abuse) of expert elicitation in support of decision making for public policy". *Proc. of the National Academy of Sciences of the United States of America 111*, 20, 7176-7184.

Nilsson, G. (2004). Traffic Safety Dimensions and the Power Model to Describe the Effect of Speed on Safety. Lund Institute of Technology, Lund (Doctoral thesis. Bulletin 221).

OECD (Organisation for Economic Co-operation and Development) (2003). Road Safety - Impact of New Technologies. OECD, Paris.

Paltrinieri, N., Tugnoli, A., Buston, J., Wardman, M., and Cozzani, V. (2013). "Dynamic Procedure for Atypical Scenarios Identification (DyPASI): A new systematic HAZID tool." *J. Loss Prev. Process Ind.*, 26, 683-695.

Roese, N. J., and Vohs, K. D. (2012). "Hindsight bias." *Perspectives on Psychological Science*, 7(5), 411-426.

Rowe, G., and Wright, G. (2001). Expert opinions in forecasting: the role of the Delphi technique. In Armstrong, J.S. (Ed.). *Principles of forecasting: A Handbook for Researchers and Practitioners*. Springer, 125-144.

Schirokoff, A., Pilli-Sihvola, E., and Sihvola, N. (2012). "Assessing the safety impacts of intersection safety systems." *Social and Behavioral Sciences*, 48 (2012), 1515-1524.

Shinar, D. (2017). *Traffic Safety and Human Behavior*. Second Edition. Emerald Publishing Limited.

Surowiecki, J. (2004). *The wisdom of crowds*. Doubleday, New York.

Tetlock, P. E. (2005). *Expert Political Judgment: How Good Is It? How Can We Know?* Princeton University Press, New Jersey.

Vaa, T., Assum, T., and Elvik, R. (2014). Driver Support Systems: Estimating road safety effects at varying levels of implementation. Institute of Transport Economics (TØI). TØI report 1304/2014. Oslo.

Virtanen, N., Schirokoff, A., Luoma, J., and Kulmala, R. (2006). Impacts of an automatic emergency call system on accident consequences. Finnish R&D Programme on Rel-Time Transport Information AINO, Ministry of Transport and Communications Finland.

Wilmink, I., Janssen, W., Jonkers, E., Malone, K., van Noort, M., Klunder, G., Rämä, P., Sihvola, N., Kulmala, R., Schirokoff, A., Lind, G., Benz, T., Peters, H., and Schönebeck, S. (2008). Impact assessment of Intelligent Vehicle Safety Systems. eIMPACT Deliverable D4. Version 2.0.

Zadeh, L. A. (1965). Fuzzy Sets. Information and Control 8, 338-353.

Figure Captions

Fig. 1. Linguistic variables on fuzzy scale (Adapted from Ehlers et al. 2017.)

Fig. 2. The three crash scenarios: (a) Scenario 1: baseline scenario with the application of two traditional RSM; (b) Scenario 2: additional application of one cooperative PSM; (c) Scenario 3: additional application of one cooperative RSM (Adapted from Ehlers et al. 2017.)

Fig. 3. Bowtie diagram for BTA1; and for BTA2 with the cooperative proactive safety measure additionally applied (Adapted from Ehlers et al. 2017.)

Fig. 4. Framework for bowtie analysis handling data uncertainty under full-range expert opinion (Adapted from Ehlers et al. 2017.)

Fig. 5. Likelihoods in BTA2 of (a) the critical event CE, (b) the outcome events OE1 and OE2, and (c) the outcome events OE3 and OE4 with simultaneously varying likelihood of the six basic events affected by the cooperative proactive safety measure in comparison to the base case

Fig. 6. Probability of occurrence of the critical event with varying likelihood of all basic events in BTA3

Fig. 7. Likelihoods of the critical event CE and the outcome events OEs in BTA4 with varying success probability of the applied traditional reactive safety measures seat belt and guardrail

Fig. 8. Event tree for the application of a cooperative system as reactive safety measure in BTA5. (Adapted from Ehlers et al. 2017.)

Fig. 9. Likelihoods of the critical event CE and outcome events OEs in BTA5 with varying estimated success probability of the cooperative reactive safety measure eCall in comparison to the base case. CE base=critical event from base case; OEx base=outcome event from base case.

Fig. 10. Likelihoods in BTA5 of (a) the outcome events OE2 and OE3, and (b) the outcome events OE4 and OE5 with varying estimated success probability of the cooperative reactive safety measure eCall in comparison to the base case. OEx base=outcome event from base case.

Fig. 11. Flowchart of the proposed bowtie approach without expert acquisition

Table 1. Basic and intermediate events used in all case studies

Basic events	Intermediate events
BE1: Intoxicated driving BE2: Speeding; insufficient speed adaptation BE3: Inattention BE4: Fatigue, falling asleep BE5: Avoiding vehicle, bicycle, pedestrian, animal, object on driveway	IE1: Driver error
BE6: Impaired visibility (in-vehicle) BE7: Steering defect BE8: Tire defect BE9: Brakes defect BE10: Suspension defect BE11: Anti-lock braking system defect BE12: Electronic stability control defect BE13: Insecure load	IE2: Vehicle malfunction
BE14: Dangerous road geometry design features BE15: Insufficient road signage or marking BE16: Poor road surface BE17: Reduced road surface friction BE18: Impaired visibility conditions (external)	IE3: Infrastructure malfunction or environmental anomaly

Source: Data from Ehlers et al. (2017).

Table 2. Basic events, reactive safety measures and outcome events for BTA1

Category	Code	Description
Basic Event	BE1–BE18	See Table 1
Safety Measure	RSM1	Seatbelt
	RSM2	Guardrail
Outcome Event	OE1base	MAIS 1-3: minor to serious
	OE2base	MAIS 3-5: serious to critical
	OE3base	MAIS 4-6: severe to fatal
	OE4base	MAIS 5-6: critical or fatal

Source: Data from Ehlers et al. (2017).

Table 3. Generated input data and literature knowledge in fuzzy scale for the input events of BTA1

Input events	State {F or S}	TFN (p_L, p_m, p_U)
BE1	F	(0.150, 0.275, 0.400)
BE2	F	(0.250, 0.388, 0.525)
BE3	F	(0.098, 0.199, 0.300)
BE4	F	(0.098, 0.199, 0.300)
BE5	F	(0.150, 0.275, 0.400)
BE6	F	(0.023, 0.074, 0.125)
BE7	F	(0.000, 0.025, 0.050)
BE8	F	(0.098, 0.199, 0.300)
BE9	F	(0.023, 0.074, 0.125)
BE10	F	(0.023, 0.074, 0.125)
BE11	F	(0.000, 0.025, 0.050)
BE12	F	(0.000, 0.025, 0.050)
BE13	F	(0.023, 0.074, 0.125)
BE14	F	(0.250, 0.388, 0.525)
BE15	F	(0.098, 0.199, 0.300)
BE16	F	(0.150, 0.275, 0.400)
BE17	F	(0.150, 0.275, 0.400)
BE18	F	(0.098, 0.199, 0.300)
RSM1	S	(0.230, 0.280, 0.330)
RSM2	S	(0.365, 0.455, 0.530)

Source: Data from Ehlers et al. (2017).
Note: BE = basic event; RSM = reactive safety measure; F = failure; S = success; TFN = triangular fuzzy number.

Table 4. Calculated fuzzy based probabilities of the output events in BTA1

Reference	Description	Likelihood		
		Lower bound (p_L)	Modal value (p_m)	Upper bound (p_U)
CE	Crash	0.839	0.977	0.998
OE1base	Minor to serious injury	0.070	0.124	0.174
OE2base	Serious to critical injury	0.091	0.149	0.209
OE3base	Severe to fatal injury	0.205	0.320	0.407
OE4base	Critical or fatal injury	0.264	0.383	0.488

Source: Data from Ehlers et al. (2017).
Note: CE = critical event; OExbase = outcome event from base case.

Table 5. Basic events, reactive safety measures and outcome events for the additional application of a cooperative system as proactive safety measure in BTA2

Category	Code	Description
Basic event	BE1–BE18	See Table 1
Safety measure	PSM1	Local danger warning system
	RSM1	Seat belt
	RSM2	Guardrail
Outcome event	OE1	MAIS 1-3: minor to serious
	OE2	MAIS 3-5: serious to critical
	OE3	MAIS 4-6: severe to fatal
	OE4	MAIS 5-6: critical or fatal

Source: Data from Ehlers et al. (2017).

Table 6. Basic events, reactive safety measures and outcome events for the application of a cooperative eCall system as additional reactive safety measure in BTA5

Category	Code	Description
Basic event	BE1–BE18	See Table 1
Safety measure	RSM1	Seat belt
	RSM2	Guardrail
	RSM3	eCall
Outcome event	OE1	MAIS 1-3: minor to serious
	OE2	MAIS 3-4: serious or severe
	OE3	MAIS 3-5: serous to critical
	OE4	MAIS 4-5: severe or critical
	OE5	MAIS 4-6: severe to fatal
	OE6	MAIS 5-6: critical or fatal

Source: Data from Ehlers et al. (2017).