Analysis of the Coupling of Communication Network and Safety Application in Cooperative Collision Warning Systems

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ABSTRACT
Cooperative collision avoidance systems rely on communication between vehicles to achieve the objective of automated or human-dependent crash avoidance. In this paper we investigate the mutual coupling of communication component and the safety application in cooperative collision warning systems. These systems are warning based collision avoidance systems that are currently under field test. We present a comprehensive co-simulation modeling framework which allows modeling and study of the entire system including vehicle dynamics, communication protocols, and collision detection/warning algorithms. Using this model, we show that in designs where the safety application and communication components are designed separately and agnostic to each other, system performance requires significantly higher network resources. Alternate content- and network-aware design strategies are shown to significantly reduce the required resources, resulting in significant reliability improvements. However, the cost of such strategies is mutual coupling of the performance of safety application and communication components. We show that such coupling can be effectively controlled in desired operation ranges for each component, leading to robust systems. The presented framework introduces a method for the study of a wide spectrum of communication dependent vehicular cyber-physical systems.

Categories and Subject Descriptors
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Algorithms, Performance, Design, Reliability

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Vehicular Networks, Collision Avoidance, DSRC, Cyber-Physical Systems, Intelligent Transportation Systems

1. INTRODUCTION
Automated collision avoidance is one of the key objectives of the efforts in transportation safety research. Autonomous driving systems inherently include aspects of automated collision avoidance; however, automated collision avoidance may also exist as a separate system and is being deployed in different flavors and complexities today. While automating collision avoidance is the ultimate objective, a key step is to enable a low cost mechanism of collision avoidance for existing human operated vehicles. The simplest forms of such applications are collision warning systems that are deployed in some high end vehicles. Cooperative Vehicle Safety (CVS) systems [1], which utilize vehicle-to-vehicle (V2V) communication, provide an ideal platform for realizing an effective and low cost collision warning and prevention mechanism. We refer to this system as Cooperative Collision Warning or CCW in this paper. This system is currently under study for regulation and government mandated deployment in the US.

Relying on communication and remote sensing in CVS allows for extended range of sensing with higher precision (since subject vehicles perform the sensing themselves, instead of being detected by a radar or camera). However, the use of communication also poses the usual challenges of unreliability in remote sensing. The mutual dependence of the communication component and the physical dynamics of the system, from safety aspects to vehicle dynamics, adds to these challenges, rendering CVS as a relatively complex Cyber-Physical System.

In CVS systems, each vehicle frequently broadcasts its state (position, speed, etc.) information, in Basic Safety Messages (BSM), to its neighboring vehicles over a wireless channel [1][5]. The wireless channel uses

Dedicated Short Range Communication (DSRC) [2][3][4]. The broadcast range of DSRC can be up to a few hundred meters. Each vehicle that receives BSMs will try to track the sending vehicles and constructs a real-time map of all vehicles in its proximity. The map is then continuously analyzed for detecting hazardous situations. In Cooperative Collision Warning (CCW) systems, which are a subset of CVS, the driver is alerted of the situation; in automated systems the vehicle can take evasive or preventative actions. Unreliability in the V2V communication network degrades the quality of the real-time map and the performance of the CVS or CCW system.

While collision warning applications and vehicular communication technologies are being extensively studied [6]-[13], their direct mutual coupling and impact has not been investigated so far (to the best of our knowledge). Our previous work on determining the mutual effect of vehicle tracking applications and V2V networks [23] provides an indirect way of assessing this effect but does not provide any mechanism of determining the impact of V2V protocols and communication performance on the actual safety parameters. This paper fills this gap and presents an elaborate framework that allows evaluating the mutual impact of different components of a CCW system.

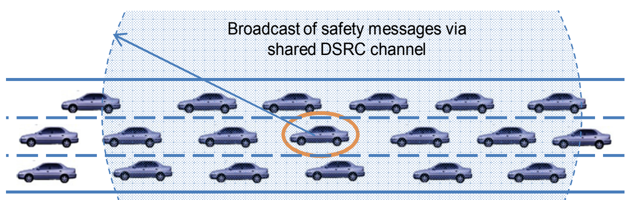

Figure 1 V2V Communications for CVS/CCW

We examine the effect of using several communication protocols [23][19][16][25] that are currently under investigation for deployment [6] on the performance of a sample CCW application. The study uses large dataset collected from a 100-car naturalistic driving field test [14] which includes over 800 trips involving near-crash or crash scenarios. The results are then analyzed to identify appropriate combination of protocols and parameters.

A key result presented in this paper is that the co-design of safety application and communication components allows for significant performance improvements over methods that separate the design of these components; the cost of this improvement is the increased mutual coupling of system components. We show that simple control mechanisms can be employed to maintain the stability of the system and curb the effects of mutual coupling.

The rest of the paper is organized as follows: section 2 presents a summary of the relevant literature on V2V communication and collision warning systems. Section 3 describes the evaluation framework, and section 4 presents abstractions and models for each component of the system that is of importance to this study. Section 5 is dedicated to evaluating the mutual impact of CCW using the models of section 4. Concluding remarks are presented in section 6.

2. RELEVANT PREVIOUS WORK

CVS systems are currently under active study [6] and are expected to be gradually deployed with government mandates. One of the main challenges of large scale deployment of CVS is the issue of scalability or communication network congestion [5][25][21][22][23]. It has been shown [5][6][25][19] that in scenarios with hundreds of vehicles in range of each other, the network performance degrades considerably, completely failing in some cases. The communication issue directly impacts the performance of safety CVS applications such as CCW. To tackle the issue of scalability several congestion control algorithms have been proposed in the literature [19][21][25][23], from which two are currently under field test (400-car tests) by the industry [6]. These congestion control methods rely on controlling the rate or power of CVS message communication to reduce the possibility of network failure. Methods such as [25][26] control the rate of message communication while methods of [21][20] target communication power control. Mechanisms presented in [19][23] (to which we contributed) use both power and rate control.

While all these methods aim at improving the network performance (e.g., lowering packet error ratio, PER), the specific metric used for rate control in [19][23][26] is the estimated vehicle position tracking error (PTE). This metric is more directly related to the performance of the safety application, than a network performance measure such as PER. This relevance leads to significant performance gains. The reason is that although a lower PER is generally thought to benefit applications such as CCW, it is shown that the timing of messages is more important than the average message rate in improving the quality of tracking other vehicles [23][19][18]. Since vehicles rely on real-time tracking of other vehicles to generate CCW alerts, the tracking error is more relevant than the network metric of PER. Similarly, it could be argued that if an application metric, directly quantifying the performance of CCW could be used for control of the network behavior, even more significant performance gains would be possible. This is one of the motivations of the work presented in this paper.

In our current study we consider the important CCW application of Forward Collision Warning (FCW). FCW targets a class of crashes that are very common and make up 30% of all crashes (potentially saving 8000 lives /year in the US alone) [28]. In fact, FCW is a low hanging fruit for transportation safety. Current FCW systems rely on radar, laser, or camera sensors to detect immediate neighbors of a car [10][11], whereas in CCW information from these sensors can be replaced by information received through BSM messages from all vehicles up to few hundred meters away (alleviating the line of sight requirement). BSM messages contain information that is usually not available through other sensors and can be used for much more complex predictions (e.g., heading changes, brake information, etc.).

There are currently several FCW algorithms in use by different manufacturers [7][8][9] (or see [10][11][13]). For the purpose of this study, we use the algorithm developed by a research consortium of several vehicle manufacturers (i.e., CAMP) [7][8]. However, the models and evaluation methodology presented here is applicable to any algorithm, since all of them essentially use the same concept of determining when action for collision avoidance is needed. The algorithm developed by CAMP [7] has used the 100-car naturalistic driving dataset [14] to determine the main crash scenarios; then a database of nearly 3,500 last-second braking and 800 last-second steering trials were used to derive the alert timing algorithms [7][8][10].

3. CVS (CCW) SYSTEM DESCRIPTION

In this section we describe the CVS/CCW system and in particular elaborate on its components and how they interact. The objective is to derive an abstract model that can be used for evaluation of the impact of communication performance on the performance of CCW applications. For this purpose we pay special attention to the communication modules and the FCW algorithm. In the rest of this document CCW and CVS are used interchangeably.

3.1 CVS/CCW System Components

CVS systems operate based on the information broadcasted in a DSRC based V2V network by each vehicle. The BSM safety messages contain enough information for a vehicle to be tracked in real time [5]. In addition to frequent BSMs that are used for vehicle tracking, CVS systems also use event driven emergency messages (e.g., for crashes or hard braking). However, the main functionality to predict and detect crashes relies on BSMs. Vehicles that receive BSMs will decode them and track each sending vehicle based on the received information; a real-time map of the neighborhood is then formed in each vehicle's situational awareness subsystem (Figure 2). The communication logic is also part of this subsystem and decides when and what to broadcast. The real-time situational awareness map is continuously analyzed by collision prediction algorithm to predict hazardous situations. If an imminent threat is detected the driver is warned (or for the case of automated systems, the car is maneuvered out of the hazardous situation). The general architecture of an in-vehicle CVS system is shown in Figure 2.

The Communication Logic in Figure 2 is responsible for determining when sampled state information is to be broadcasted; this component also decides the power (range) of transmission. Congestion control algorithms [19][25][20][26] will control these decisions.

The Collision Detection module implements algorithms for applications such as Forward Collision Warning. In this paper we consider how the communication logic, the underlying radio module and the vehicle tracking component impact the final output of the system through the collision detection module.

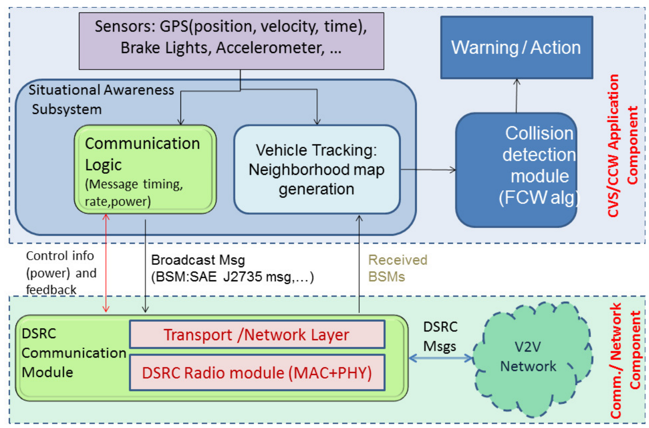

Figure 2 CVS in-vehicle system architecture

3.2 FCW Algorithm

Forward collision warning algorithms are designed to alert the driver in situations where the current movement pattern of vehicles makes a crash imminent. The alert timing should be such that the driver reaction time is taken into account, but is not too soon to cause false alarms or alert a driver that may react on his/her own without the warning. Striking such a balance is a complicated task and has been the subject of numerous studies [7]-[13].

For this study we selected the *CAMPLinear* algorithm from [7], which has been designed using data from a large dataset of driver reactions to dangerous situations. The alert timing is designed such that a warning is given just before it becomes necessary for the driver to take an evasive action. The alert timing is generally described as a "warning range", which continuously changes as the speed, acceleration and distance between vehicles change. If the distance between a Leading Vehicle (LV) and a Following Vehicle (FV) becomes less than the warning range, a collision warning should be issued to the FV. The equations from which the warning range, r_w, is derived are summarized below for a brief discussion, details are found in [7][8][10]. The calculations use speed and acceleration data of LV and FV (i.e., $v_{LV}, a_{LV}, v_{FV}, a_{FV}$). Using this data, r_w is calculated as a sum of Brake Onset Range (*BOR*) and driver+system reaction range r_d:

$r_w = BOR_n + r_d$

$$r_d = (v_{FV} - v_{LV})t_d + 0.5(a_{FV} - a_{LV})t_d^{\,2}.$$

Where t_d is the driver and brake system reaction delay (~2.5s). BOR is computed for three different scenarios below:

1) LV stationary at the beginning and end of scenario
2) LV moving at the beginning and end of scenario
3) LV moving at the beginning but stopping at the end

$$BOR_1 = (v_{FVP}^{\;2})/(-2d_{rqd})$$
$$BOR_2 = (v_{FVP} - v_{LVP})^2/(-2(d_{rqd} - d_{LV}))$$
$$BOR_3 = \frac{v_{FVP}^{\;2}}{-2d_{rqd}} - \frac{v_{LVP}^{\;2}}{-2d_{LV}}$$

Where v_{FVP} and v_{LVP} are the predicted velocity of FV and LV after a t_d and are simply found as:

$$v_{FVP} = v_{FV} + a_{FV}t_d \quad and \quad v_{LVP} = v_{LV} + a_{LV}t_d.$$

and d_{LV} is the deceleration of LV; d_{rqd} is the deceleration that is required at the FV for avoiding a crash and is modeled in ([6][7] using actual human reaction data, as follows (in ft/s^2):

$$d_{rqd} = -5.3 + 0.68a_{LV} + 2.57(v_{LV} > 0) - 0.086(v_{FV} - v_{LVP})$$

It must be noted that the FV always has precise information about its own state (position, speed, acceleration), but only an estimate of LV state. In CCW such estimate is through the real-time tracking over DSRC network. This means that all values of v_{LV}, a_{LV} above have to be replaced by network estimates $\tilde{v}_{LV}, \tilde{a}_{LV}$. It is also intutively seen from the BOR equations that tracking error ($v_{LV} - \tilde{v}_{LV}$ or $a_{LV} - \tilde{a}_{LV}$) will not be dampenned as they directly show up in the final equations with comparable weight to the FV values.

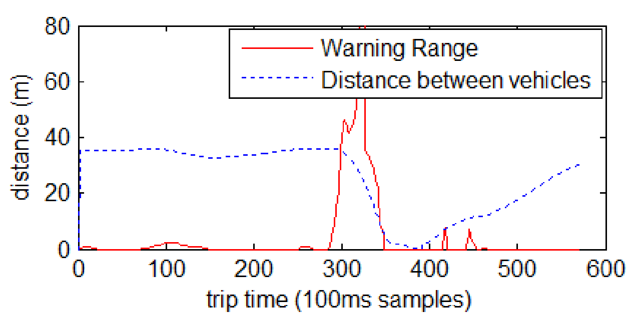

Figure 3 Example of warning range derived from CAMPLinear algorithm, produced on data from a near crash scenario from 100-car dataset.

Figure 3 shows the results for a sample scenario from the 100-car dataset [14]. Here we followed the model in Figure 4 and applied the above equations to derive the warning range (assuming ideal communication). When the warning range becomes greater than the distance between vehicles, the warning generation algorithm is notified to present the driver with an alert. Repeated notifications are aggregated by the warning generation algorithm (every ~2-3s).

4. SYSTEM MODELING FOR PERFORMANCE EVALUATION

To examine the effect of different components of the system on each other and the overall outcome of the CCW, we need to model the system in an abstract form. Figure 4 shows the co-simulation modeling framework that we have developed for this purpose. This framework allows plugging in sub-models of different complexity to study the system in different detail levels. It is also possible to use different datasets for evaluating the system.

The evaluation framework uses models for components such as communication and CCW application. The CCW application, which is FCW here, is simple to model as it only involves relatively straightforward calculations; however, the communication model can become very complex as it has been observed in our other recent work [22][24]. A communication model can be as elaborate as a simulation model, or defined in abstract mathematical forms [22][24]. In this paper we use mathematical models (already verified using simulation) since they allow much faster runtime. The runtime when involving communication simulations (such as ns-3 models) increases several orders of magnitude. The next sections describe the model of the communication component, including communication logic (strategy) and DSRC network, and a model of the CCW application. For each of these models we are specifically interested in performance metrics and configurable parameters, in order to be able to derive an optimization or control framework that allows improving the performance of the system.

We use this framework with the input data from the 100-car naturalistic driving field test [14] that included hundreds of crash or near crash vehicle dynamics. Since this dataset only includes data for one of the vehicles involved, we use proven car-following models (used in MITSIM [15]) and developed by [15] to derive the dynamics of the FV, assuming that LV dynamics are extracted from the 100-car dataset. While this is one method of evaluating the system, the framework allows for directly inputting data for both LV and FV from a dataset. However, at the time of this writing such database was not available to us and is not included in this study. Since the absolute outputs of the system will be to a great degree dependent on the dataset used, we treat the results in relative sense and for comparison of communication methods, rather than for deriving absolute measures.

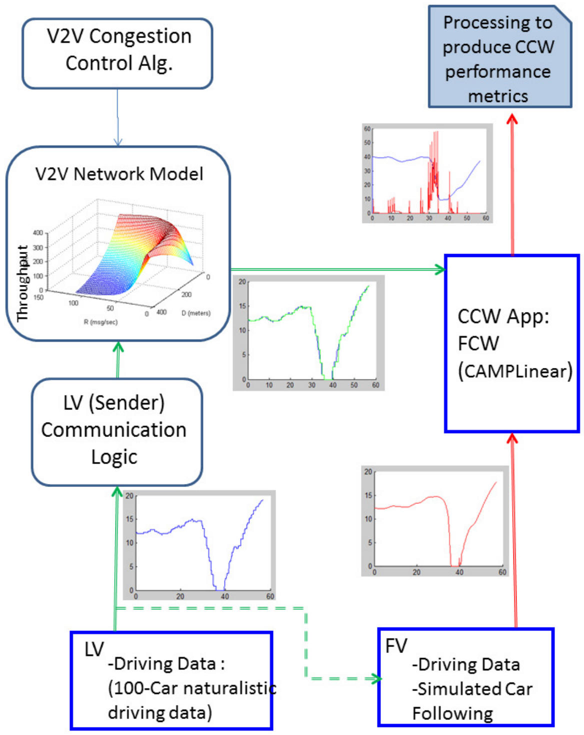

Figure 4 CCW Evaluation and Modeling Framework

4.1 Collision Warning Performance Metrics

The FCW application in each vehicle is assumed to be a continuously running process analyzing the situation every T_{cw} seconds (T_{cw} =100ms). At each time instance, the current warning range $r_w(t)$ and the distance $d(t)$ between LV and FV are compared and if $r_w(t) > d(t)$, the user interface is notified to generate a warning (which ignores further notifications for ~2sec after the last notification). To study the effect of different system parameters, we need to compare the output of the hazard detection and warning algorithm for those parameters. For this purpose a metric that can indicate how well the system is performing is needed. While there is no universally agreed to metric for measuring the performance of FCW algorithms (or other collision avoidance), [13] provides a reasonably good method of quantifying the performance of FCW. Metrics such as precision, true positive (*TP*), true negative, false positive, false negative, and Accuracy (*A*) are defined in [13]. We use two of these methods in this paper, since all of them provide similar results (as we observed in our simulations). Accuracy and True Positive are defined using the following formulation:

$TP=Ch/(Is+Ch)$
$A = (Ch+Cs)/(Is+Ih+Ch+Cs)$

where *Ch* and *Cs* are the numbers of correctly predicted hazard and safe indications; *Is* is the number of incorrectly predicted safe indications (misidentified actual hazards), and *Ih* is the number of incorrectly predicted hazard indications (misidentified actual safe situations). *Accuracy* gives an overall measure of the accuracy of the system in generating or not generating a warning [13].

4.2 V2V Network Model

The V2V network can be modeled at different levels of complexity. We presented a *hybrid systems* based model for CVS, including its networking component in [24]. However this hybrid system model is too complex for the needs of the evaluation framework in this paper. Alternatively, we propose to use the stochastic model of the CVS network in [22]. This stochastic model provides a numeric method of calculating probability of message reception at different distances from a sender for a wide range of CVS parameters, such as rate and range (power) of transmission, MAC parameters, and road density. This model is abstract enough to be used in the evaluation framework of Figure 4. To use this model, we can construct queries of the form PER = $E(R,P,\rho,d)$, to get the value of packet loss rate at distance *d* from the sender for rate *R* and power *P*, in a road with density ρ. While we can generally assume certain values of PER and evaluate CCW, for congestion control algorithms that control different values of rate and power to achieve a specific PER, it is more informative to see how *P* and *R* directly affect CCW (This is the subject of another study and is not presented here). Therefore for cases where we are not concerned with the congestion control algorithms, we can rely on modeling the V2V network with a random loss rate (PER) and inflict that random loss on the information that is transferred from LV to FV.

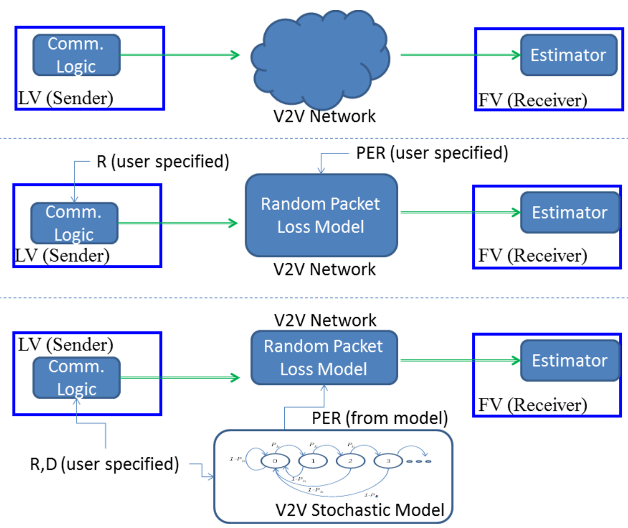

Figure 5 Abstracting V2V network model

4.3 Communication Logic (Policies)

A communication policy describes how the DSRC network is used for exchange of vehicular information. In particular in the CVS setting, the communication policy or logic has to determine when a message should be broadcast and the power associated with each transmission. The choice of the power will normally determine how far the message reaches, but it also has a direct effect on the PER of all nodes as higher power means more interference. A V2V network model such as the one in [22] already captures this effect. Similarly the average selected rate of transmission also affects PER and is captured by the model in [22].

An important aspect of the communication logic is the timing of each message which is not directly clear from a measure such as rate. Therefore in our modeling of the communication logic we need to properly model this decision. Here we consider three prominent choices from the literature (Figure 6): choices of Periodic Beaconing (PB) ([5]), Error-Dependent policy (ED) ([16] inspired by [18]) and Error-Dependent Network-aware (EDN) policy [19][23]. Methods in [5] and [19][23] are currently under study by industry for standardization.

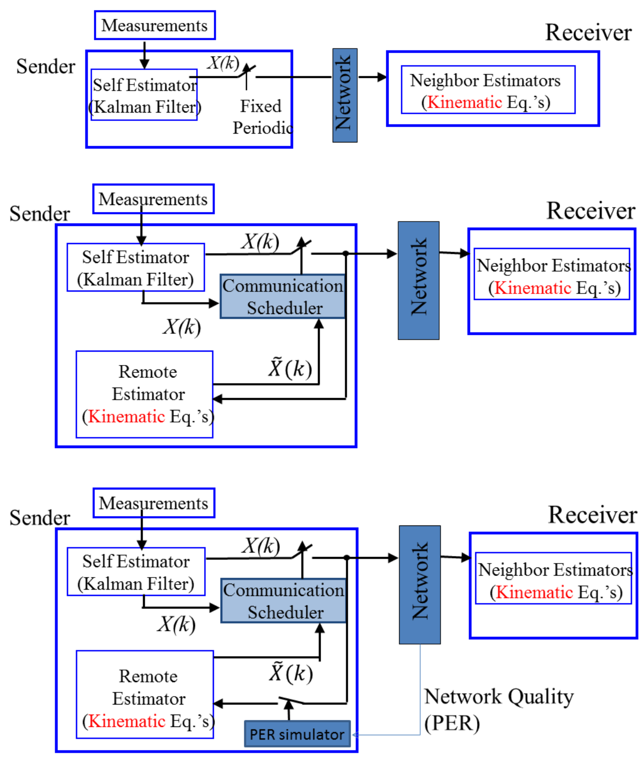

Figure 6 Communication Logics: (top) Periodic Beaconing, (middle) Error-Dependent, (bottom) Error-Dependent and Network-Aware

The periodic beaconing (PB) policy uses a simple content unaware mechanism of periodically sampling the signal and transmitting it over the channel. The error dependent policy is much more complex and uses the concept depicted in Figure 6. For error-dependent transmission, a sender locally simulates the estimator of the receiver (remote estimator) to understand receiver's error in estimating sender's position. If this error is found to be greater than a threshold (E_{th}), the sender (scheduler) sends a new message with updated data to correct the receiver's estimator. This method is shown to significantly reduce the required rate of message generation while maintaining the same estimation error at the receiver [16]. Kinematic models used in ED estimators may be 1st or 2nd order (constant speed or constant acceleration). We use the latter in this paper. The ED method does not take into account the possibility of the transmitted packet being lost. The EDN method enhances ED by applying a simplified network simulator that inflicts losses (with the same PER experienced by the receiver) on the local copy of the packets that are given to the local "remote estimator". This way, the remote estimator will more closely follow the behavior of the estimator at the receiver. EDN requires approximating PER. The approximation can be done using the mathematical model in [22] or by directly observing and averaging PER from all senders in a region.

5. COUPLING OF COMMUNICATIONS AND SAFETY APPLICATION

The impact of safety application on network performance can be modeled using network models such as our previous work in [22]. The impact of communication on application can be numerically derived using the framework in Figure 4. To get more insight, we first assume that the communication performance is independent of the safety application and examine the impact of communication performance on safety applications, using the FCW example. We consider both network-agnostic and network-aware safety applications and show the performance gain of network-aware communication logic in the application. We then examine the actual situations in which communication is impacted by the application load. We study the coupling of components as a result of adding network awareness in the application and investigate possible methods of containing the consequences of coupling.

5.1 Effect of Communication Network Performance on Safety Application

From an application perspective, the effect of lower communication layers (transport and below) is seen only as a pattern of packet error and delay imposed on the stream of messages sent by the LV. Since the V2V safety network uses a single hop broadcast network, the unreliability in communication will be only due to MAC and PHY issues. Message loss in distances up to 200 meter is mostly due to MAC issues, as fading is not strong enough to inflict significant packet error at these distances when maximum power is used [27]. At higher distances and especially when line of sight is blocked, fading plays a much bigger role. Given these facts, and knowing that the CSMA/CA losses are well randomized [22], we can model the effect of communication as random loss. Delay is not of concern in single hop DSRC broadcast network since EDCA ensures a packet is sent out in less than CW (contention window size) count downs even in a fully utilized network, despite the high risk of packet collision. Therefore, to get an insight into the effect of communication performance on safety application we can consider the effect of different loss rates on safety applications that use different communication logics (Figure 2).

As a first step, we use the co-simulation framework and derive the performance of the baseline design of CCW, in which periodic sampling and communication at 10Hz is used. By varying the rate of sampling from 2Hz to 10Hz, and varying PER from 0 to .8, we can see how the amount of delivered information affects the application performance. Figure 7 and report the results, averaged over the 800 scenarios of [14]. Figure 7 reports *Accuracy* and *True Positive* values for all combinations of rate and PER.

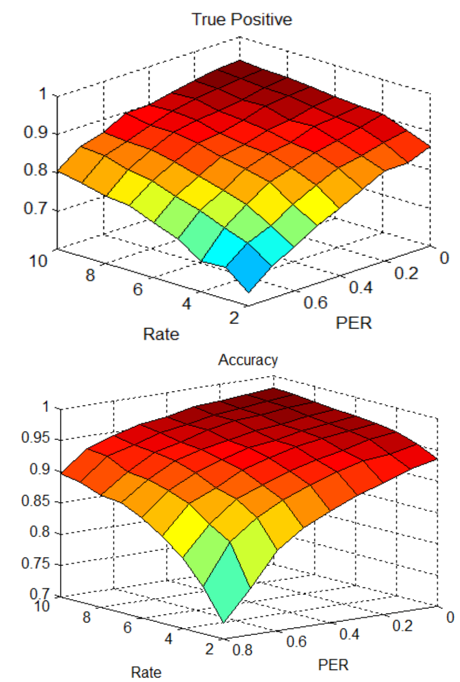

Figure 7 FCW *Accuracy* and *True Positive* for different values of PER and message rates (PB policy)

It can be observed that reception rates above 5 or 6 Hz result in *Accuracy* of above 95%. (or True Positive ratio > 90%) It must be noted that accuracy at these high levels are necessary for generation of correct warnings. The maximum *Accuracy* of near 98% is achieved at 10Hz with no loss, since the FCW detection algorithm is setup to run at 10Hz and provides the ground truth. We must note that

Given the similar trends in *true positive* ratio and *Accuracy*, and space limitation, we only show the results for *Accuracy* in the remainder of this paper.

5.2 Effect of Communication Logic/Strategy

We next examine the ED and EDN communication logics to see how the performance could be improved by introducing content awareness (through ED) and network awareness (through EDN) into the communication logic of the safety application.

To compare the performance of different application layer communication logics under unreliable operation of the communication network, we setup an experiment in which the rate of information generated by each algorithm is at its ideal level (producing near zero tracking error at the receiver when PER =0), and then vary PER to change the rate of information received by the receiver. The results are compared by measuring both *Accuracy* and the Position Tracking Error (PTE) in each case. We note that while *Accuracy* is a safety application performance measure, PTE can be viewed as a performance measure for the situational awareness subsystem. Results are depicted in Figure 8.

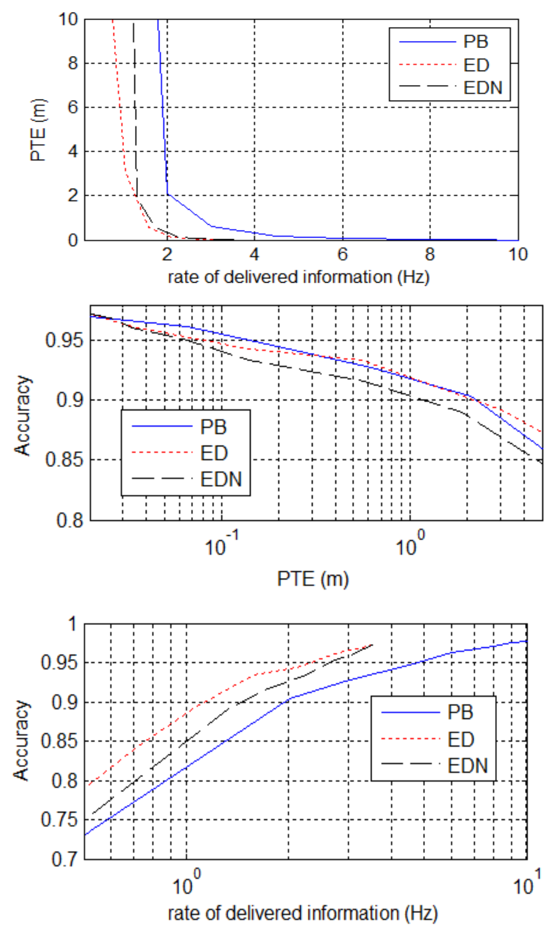

Figure 8 Comparing the performance of different communication logics: PB, ED and EDN.

It can be observed in Figure 8 (PTE vs rate of delivered info) that to achieve a very low PTE (under 50cm), ED and EDN only need around 2.5Hz of data to be sent, while with periodic beaconing a rate of above 5-6Hz is needed. This is in line with what has been observed in other works [19]. Examining the results for *Accuracy* versus PTE in Figure 8, we see that under all algorithms the FCW algorithm perform similarly if the PTE is maintained at the same level. However, maintaining PTE requires a different rate of messages to be available at the receiver as is seen in the first plot of Figure 8; the last plot relates *Accuracy* to the rate of delivered information to provide a better comparison. It is observed that ED and EDN can use a much lower level of information at the receiver to reach desired *Accuracy* levels of above 0.95.

It must be noted that while ED and EDN appear to be performing similarly (ED even requiring a lower rate of received information), the comparisons in Figure 8 may be misleading since we are looking at the rate of information at the receiver. When compared under different PER levels, the ED algorithm is unable to keep up with the losses in the network, while EDN manages to maintain the desired rate at the receiver by adjusting its transmission rate. The results, depicted in Figure 9, show that EDN always maintains a higher *Accuracy* under all PER conditions. This is in particular more evident at PER values above 0.5. We note however that a proper comparison of ED and EDN requires studying their effect on the network as well, which will be discussed in the next section.

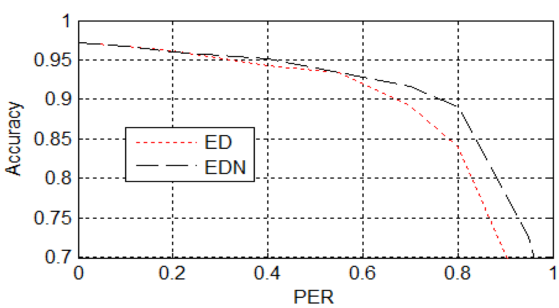

Figure 9 Performance of ED and EDN under different communication PER levels (*Eth*=0.1)

To get a more complete picture of how these algorithms differ, we plotted the *Accuracy* and rate of information generated by these algorithms under different PER and tracking error threshold values in Figure 10 and Figure 11. The results show that at high PER, EDN manages to keep the value of *Accuracy* higher, even for the cases where the threshold value is large, while *Accuracy* values for ED goes down to 55% (as opposed to 65% for EDN). In general it is seen that these policies achieve significantly more robust results, compared to PB for a wider range of rates.

5.3 Coupling of Components

From Figure 10, it is seen that the EDN policy increases the rate in response to increase in PER in the network to ensure enough data is available at the receiver. The effect of this increase is increased *Accuracy* values generated from the same experiments (Figure 11). Given that network performance is a function of the offered load, this increase in load will result in increased network PER, which in turn may cause EDN to send even more information. This coupling causes a positive feedback cycle that should be controlled to prevent the system from entering undesired operation regions.

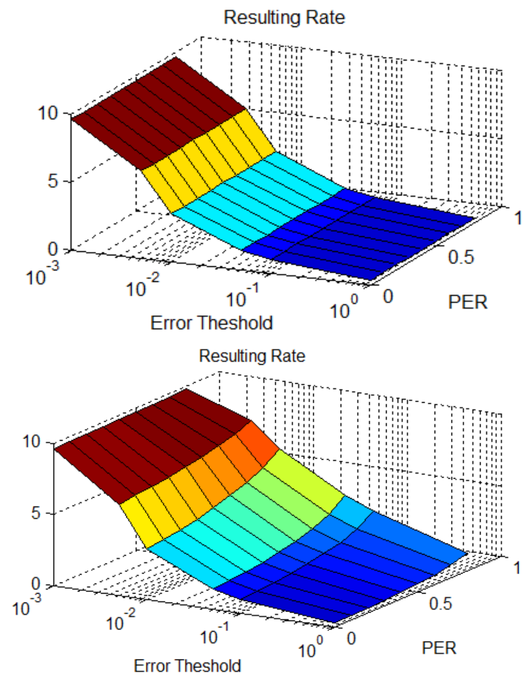

Figure 10 Rate of message generation in Hz for ED (top) and EDN (bottom) communication logics

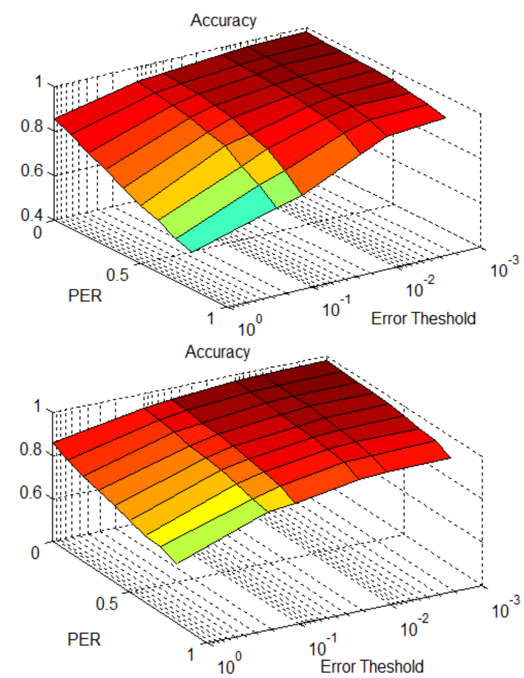

Figure 11 CCW performance (*Accuracy*) of ED (top) and EDN(bottom) policies for different *PER* and error threshold values

To understand the effect of this coupling, we derive the system performance (*Accuracy*) using an actual network model from [22]. Using this model, it is possible to capture the change in network performance (i.e., the resulting PER) as the message rate offered by EDN changes. Figure 12 shows the result for different road densities. Note that at higher road densities, the PER changes due to increase in the number of interferers). As road density (and PER) increases, EDN increases its rate, but fails to maintain *Accuracy* due to further increased PER. The overall result is that EDN will not perform better than ED. A simple method to overcome this issue is to control the number of interferers by controlling the range (power) of transmission inversely proportional to road density; this concept is similar to more complex and actual power control methods such as the one proposed in [19]. This is shown as "EDN+power control" in Figure 12. We use this simple method to avoid complicating the analysis. This basic method allows the *Accuracy* to be maintained at around 0.97 as PER values grow (seen beyond density of 0.4).

This method inserts a feedback control scheme that counters the negative impact of coupling. While such methods have been studied in literature before [19][23], this paper is the first work to quantify and study the coupling from safety application perspective.

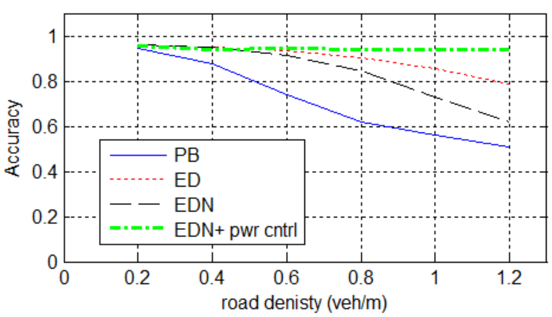

Figure 12 Performance of FCW under different highway densities, for different CVS designs

6. CONCLUSIONS

In this paper we presented a simulation/numerical modeling framework that describes the entire CCW system in one unified model, allowing for evaluation of the effect of multiple components on each other. We are in particular interested in the impact of communication component on the performance of CCW, and the coupling that may exist between communication networking component and the safety application. We use numerical and co-simulation models to study the system. A large dataset of naturalistic driving scenarios, along with simulated driving patterns, are used in this study to identify the effect of different setting and performance levels of communication component on accuracy of collision warnings generated by CCW. It was shown that introducing content and network awareness in the communication logic of the safety application results in significant performance gains for CCW systems. This gain comes at the cost of coupling the behavior of safety application and the communication network. To contain the possible negative effects of the coupling a simple interference management scheme is employed and shown to be very effective.

The study presented here is the first such study to the best of our knowledge. The modeling framework allows for expanding the study to other CVS and cooperative automated driving applications. The model is being integrated with network simulators such as ns-3 and is currently used by industry as the basis for more complex safety application evaluation and calibration platforms.

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