

APPENDIX C

ANALYSIS OF FORWARD COLLISION WARNING PERFORMANCE METRICS USING REAMACS

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C ANALYSIS OF FORWARD COLLISION WARNING PERFORMANCE METRICS USING REAMACS

C.1 Foreword

To help identify and understand the important parameters of countermeasures in rear-end crashes, modeling and simulation work was performed and reported using the computer tool REAMACS (Rear-end Accident Model and Countermeasure Simulation). This work was done in 1997, early in the project, and made use of the best available information at the time. The results influenced direction on choosing the Alert Zone maximum longitudinal extent, the need for FCW systems to estimate lead vehicle deceleration, and deepened the understanding of the tradeoffs between providing maximum warning capability while not producing so many nuisance alerts that driver acceptance is negatively affected.

- Because the modeling work was completed early in the project, the reader should keep in mind the following while reading:
- In this document, “cautionary” and “imminent” alert warning algorithms refer to two specific warning algorithms. These are both based on closing speed, and were assumed to be candidates for specifying alert onset requirements for a single-stage alert. “Imminent” alert does *not* correspond to the proposed alert onset timing requirements of Chapter 4, nor does “cautionary.”
- The alert onset timing requirements proposed in Chapter 4 are not specifically included in this appendix’s analysis. These requirements were developed in the final stages of the project and a re-computation of these results is outside the project scope. The algorithm closest to the type of timing requirements suggested in Chapter 4 may be the “lead vehicle deceleration” algorithm with a parameter set “RT=1.5 sec, asv = -0.3g”.

C.2 Summary of Findings

This document reports modeling and simulation work that estimates performance measures of Forward Collision Warning (FCW) systems.

This work studies relative performance effects of warning algorithm types, maximum warning ranges, and sensitivity to modeling assumptions. Warning algorithms considered include a first (earlier) alert, the “cautionary” crash alert, and a second set of parameters to define a second (last-moment) alert, termed the “imminent” crash alert. Performance metrics are computed here for a FCW that issues *single* alerts based on various warning algorithms, including the cautionary and imminent crash alerts as well as basic variants of these designs. Also included are warning algorithms that make use of lead vehicle deceleration information.

The metrics used to compare performance of countermeasures are the potential to reduce relative harm, and the relative frequency of in-path nuisance alerts. Relative harm is computed over a set of potential rear-end crash scenarios; relative harm is defined as the ratio of the sum of squared impact speeds in crashes with vehicles equipped with a FCW system to the same metric computed for vehicles not equipped with a FCW. In-path nuisance alerts are alerts triggered by vehicles in the path of the host vehicle in situations that the driver does not regard as alarming. The modeling work assumes perfect sensing by the FCW system and 100% compliance of drivers to warnings. It is argued, however, that to understand the likely benefit of FCWs in practice, future work is needed to consider the possible effects that nuisance alerts may have on reducing driver usage and compliance with the crash warning system. This report does not attempt to include these effects and reduction in harm and in-path nuisance alerts rates are computed separately.

The modeling work here builds on a simulation tool named REAMACS, which has been developed and used at Ford since 1993. REAMACS is an acronym for Rear-end Accident Model and Countermeasure Simulation. Simulation results are based on rear-end crash scenarios generated using a database of actual vehicle pair speeds and headways collected from Interstate 40 near Albuquerque by the Federal Highway Administration (FHWA). This is the only comprehensive database available to CAMP at this time, and it is not known to what degree the reliance on this database has biased the simulation results. The database was generated using loop detectors, and thus leads to a simulation crash set with a significant under-representation of rear-end crashes in which the lead vehicle is stopped when struck. Also, the database is highway data and therefore may not represent vehicle pair behaviors characteristic of other roadway types.

Simulation work findings include:

1. A target sensor that can support warnings at a 75-meter range provides 93% of the benefits of a sensor with unlimited range. A more accurate representation of stopped lead vehicle situations, however, might indicate that there are benefits of a longer working range.
2. There is a potential for FCWs to reduce relative harm by up to 67 percent using the cautionary crash alert as the only warning, along with a sensor that supports a 75 meter warning range. When used as the only warning, the imminent crash alert has a potential to reduce relative harm by only 20% – this alert occurs too late for much benefit with decelerating lead vehicles. Effectiveness estimates may decrease when considering the effects of nuisance alerts on driver usage of, and compliance with, FCWs.

When lead vehicle information is considered, there is a potential to reduce relative harm up to 81% using a set of algorithm parameters corresponding to both the cautionary and imminent parameters, and a sensor that supports a 75 m warning range.

3. Estimates of the expected exposure of a driver to in-path nuisance alerts are sensitive to modeling assumptions regarding braking levels that drivers are comfortable using in situations they consider non-alarming. For the cautionary crash alert design, a

rough scaling analysis estimates that 28 in-path nuisance alerts would occur for every rear-end crash with an impact speed of ten miles per hour or greater. This scales to one in-path nuisance alert per 4.2 years per vehicle. The imminent crash alert design leads to only 1.3 in-path nuisance alerts per rear-end crash with at least a ten mile per hour impact speed. This illustrates a tradeoff between increasing the potential to reduce relative harm and reducing the estimated in-path nuisance rates. Future experimental work is needed to allow more accurate scaling from in-path nuisance alert rates computed in simulation to rates likely to be seen in practice. Thus in-path nuisance alert results should be used only for comparison between countermeasure designs.

4. The simulation work suggests that information about a lead vehicle's deceleration level can improve the performance of a FCW system. By adding lead vehicle information to the imminent crash alert, the potential for reduction in relative harm increases from 20% to 81%, however, the corresponding in-path nuisance alert rate increases from 1.3 to 13.5 per rear-end crash with impact speed of ten miles per hour or more. By adding both lead vehicle deceleration information and varying the warning algorithm design, a potential reduction in relative harm nearly equal to that of the cautionary crash alert can be achieved (79%). While the in-path nuisance rate drops from 28 to 2.3 alerts per rear-end collision with impact speed of ten miles per hour or greater.

In practice, in-path nuisance alert rates may be different than reported here for warning algorithms that use lead vehicle deceleration information. There are two reasons. First, this work studies a particular class of such warning algorithms, which is those algorithms that assume the lead vehicle will continue braking at its current deceleration until it stops. The simulated situations, however, match this same scenario – the lead vehicle brakes completely to a stop. In practice, many nuisance alerts will occur for these algorithms when the lead vehicle brakes only momentarily, and so the in-path nuisance rate is likely to be higher in practice for this set of algorithms. Second, warning algorithms can use different assumptions about the future braking levels of the lead vehicle. These other algorithms are not studied here.

The simulation results suggest it is possible to define a FCW warning algorithm capable of triggering alerts which are timely enough to significantly reduce rear-end crash harm while not producing so many in-path nuisance alerts that drivers reject the system, nullifying any overall benefit. This conclusion is based on a proposed model that defines alarming situations by the braking levels necessary to avoid a collision. Results of the ongoing human factors experiments portion of this Project will provide a sounder basis for such models, and may affect the conclusion.

There is a lack of comprehensive field data on actual vehicle-following and braking behavior. More data is needed to improve confidence in predictions of potential benefits of FCW deployment.

C.3 Introduction

This study was produced as part of the Development and Validation of Functional Definitions and Evaluation Procedures for Collision Warning/Avoidance Systems Project, which is a cooperative effort between the Ford/General Motors Crash Avoidance Metrics Partnership (CAMP) and the National Highway Traffic Safety Administration (NHTSA). The purpose of this project is to accelerate the implementation of automotive rear-end crash avoidance countermeasures [1]. The main purpose of the modeling and simulation work reported in this document is to support the definition of functional requirements for forward collision warning systems (FCWs).

The work reported here uses two primary metrics associated with rear-end countermeasure performance. The first primary metric is the *potential reduction in relative harm* that FCWs may provide. Relative harm is computed over a set of potential rear-end crash scenarios; relative harm is defined as the ratio of the sum of squared impact speeds in crashes with vehicles equipped with a FCW system to the same metric computed for vehicles not equipped with a FCW. Consider a “subject vehicle” (SV) which is following another vehicle, which will be called the “principal other vehicle” (POV). Let V_{sv} and V_{pov} denote the speeds of the SV and the POV, respectively, as shown in Figure 1, so that if a rear-end collision occurs, the impact speed is $V_{sv} - V_{pov}$. The terms “subject vehicle” (SV) and “following vehicle” could be used interchangeably, but this report uses “SV”. Likewise, the terms “principal other vehicle” (POV) and “lead vehicle” could be used interchangeably, but again, this report uses “POV.”

Let A denote a set of potential rear-end crash scenarios. Then the relative harm associated with a particular FCW can be expressed as:

$$\text{Relative Harm} = \frac{\sum_A (V_{sv} - V_{pov})^2 \text{ with FCW}}{\sum_A (V_{sv} - V_{pov})^2 \text{ without FCW}} \times 100\%$$

The reduction in relative harm associated with a countermeasure or algorithm is expressed as a percent reduction in relative harm:

$$\text{Reduction in Relative Harm} = 100\% - \text{Relative Harm}$$

The potential for reduction in relative harm for an effective countermeasure is then between 0% (no effect) and 100% (all crashes eliminated). The word *potential* is a qualifier to indicate

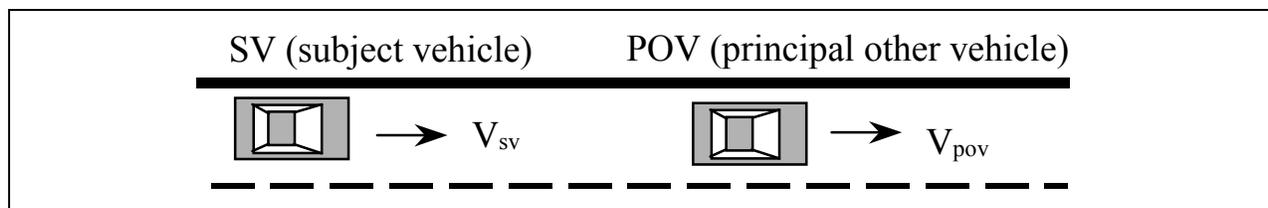


Figure 1 Vehicle Pair Illustration

that the reductions in harm conveyed by the simulation results are only provisional and that realizable reductions in harm depend on many operational and psychological factors not considered here. The potential for reduction in relative harm is used to make relative comparisons between different countermeasure designs, and is intended to provide insight into how different countermeasures might impact actual harm occurring in real-world collisions. Reduction in the number of crashes is also reported in this document since some researchers use this metric instead of harm.

The second primary metric is the *relative frequency of in-path nuisance alerts* that may result from use of FCWs. For this report, an in-path nuisance alert is defined as an alert issued by a FCW in response to a POV located in the host vehicle's path, but issued in a situation considered by the driver to be non-alarming. In-path nuisance alerts are likely to occur for any FCW since the countermeasure must issue alerts in time for an inattentive driver to take preventive action, and countermeasures currently cannot distinguish between drivers unaware of impending danger and drivers aware of the situation.

The results for potential reduction in relative harm reported in this document do not take into account the possible effect of nuisance alerts on the willingness of drivers to heed the warnings or even to use the system. Therefore the results reported here are only a first-order estimate of benefits, and may be an upper bound on the actual benefits that may occur with deployment. A key premise of CAMP, is the *realizable reduction in relative harm*; that would result from the deployment of FCWs, would depend not only on the apparent benefits, but also on the possible effect of nuisance alerts, on the willingness of drivers to use a FCW and heed the warnings. The benefits accrued when considering this effect might be called "second-order" benefits.

Figure 2 illustrates the concept of factoring in-path nuisance alerts into estimates of realizable reductions in harm. The solid line in the figure represents the estimates made in this report, as well as in similar work by others – the potential for reduction in relative harm is computed assuming ideal compliance and 100% use of FCWs. This apparent reduction in relative harm can be made to increase by changing warning algorithm design to provide

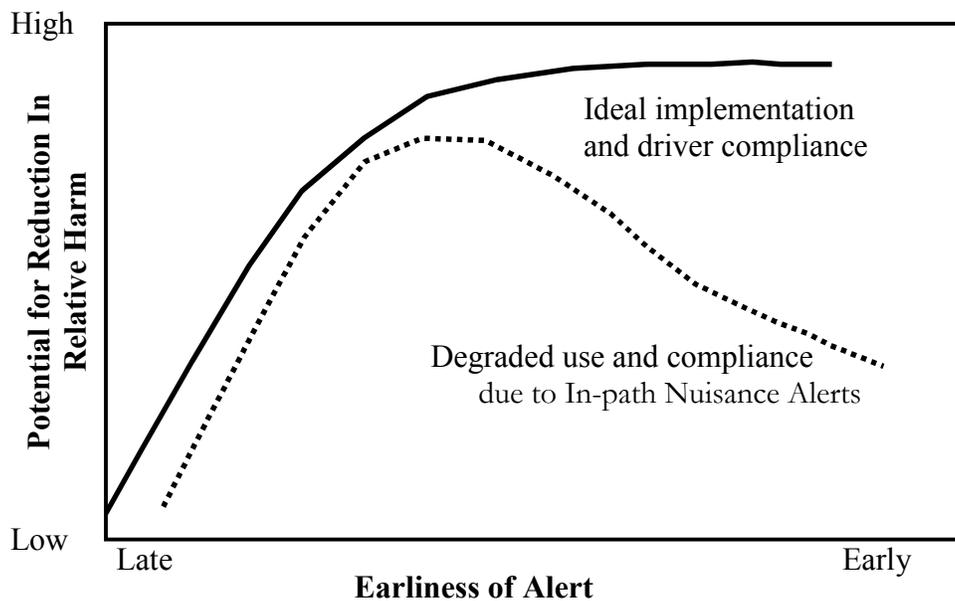


Figure 2 Possible Effect of FCW In-Path Nuisance Alerts in Reducing Realizable Reductions in Harm

earlier alerts. With earlier alerts, in-path nuisances will tend to increase, perhaps discouraging drivers from using the system and/or complying with warnings. The effects of nuisance alerts on overall system effectiveness are not well understood; one possible effect is illustrated in Figure 3, in which usage and compliance of a FCW is shown to decrease with earliness of the alert. To compute a realizable reduction in harm, the nuisance alerts must be factored into the assumed levels of deployment, usage, and compliance. The dotted line in Figure 2 illustrates the net realizable reduction in relative harm that would result if nuisance alert effects like that shown in Figure 3 are considered. This estimation of second-order benefits is not completed in this report. The first-order results reported do provide information, however, that may be used with the results of the human factors studies currently underway to estimate a realizable reduction in harm.

The simulation results reported here are based on the use of REAMACS (Rear-end Accident Model and Countermeasure Simulation). REAMACS uses headway and vehicle speed field data, processed with experimentally based models, to generate a set of vehicle

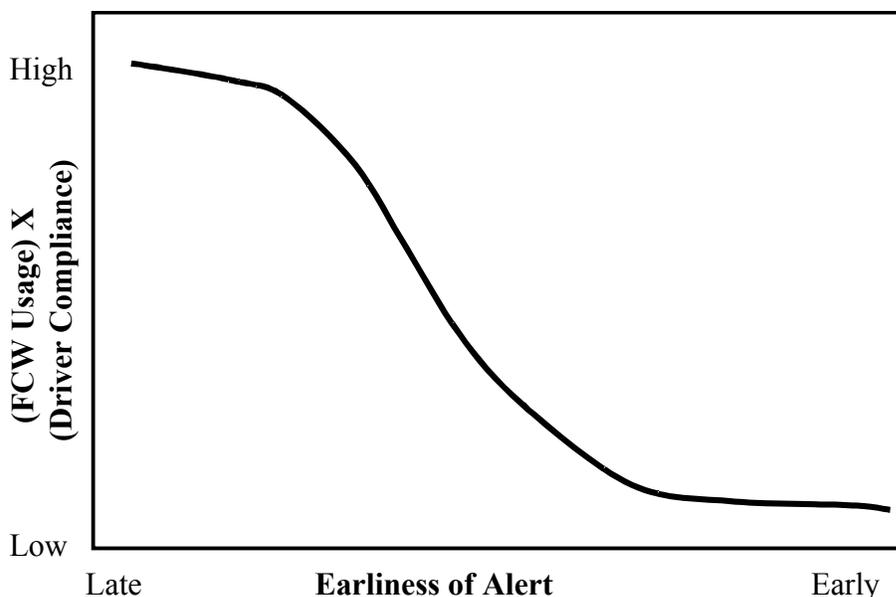


Figure 3 Concept: In-Path Nuisances May Reduce FCW Usage

pairs with potential to become rear-end collisions. Actual vehicle pair speed and headways collected from Interstate 40 near Albuquerque by the Federal Highway Administration (FHWA) are used as initial conditions for vehicle pairs. Computer simulation introduces POV braking for each vehicle pair from the database, and statistical distributions of SV driver reaction time and POV braking level are used to evaluate the outcome of the scenario. The effectiveness of a collision warning can then be estimated. The modeling work assumes perfect sensing by the FCW system and 100% compliance of drivers to warnings. By studying the variation of performance for different rear-end collision warning algorithms, algorithm parameters, and target sensing ranges, insight is gained into practical design issues as well as higher level issues of technical feasibility and upper bounds of possible deployment benefits. The modeling approach continues work on REAMACS by Farber and colleagues at Ford [2][3][4][5][6][7]. This earlier work and other studies [8][9] have contributed first-order estimates of the potential reduction of relative harm from use of FCWs. The present document contributes a definition of in-path nuisance alerts, and develops a method to estimate in-path nuisance alerts, thereby providing information for possible estimation later of second-order benefits.

The exclusive use of the FHWA database in generating vehicle pair conflict situations introduces two important caveats into any interpretation of the simulation results. First, while the database is the only comprehensive database available to CAMP at the time of these analyses, the database is generated using loop detectors, and thus no vehicle acceleration data is available. With REAMACS, then, this leads to a simulation crash set with a significant under-representation of rear-end crashes in which the POV is stopped when struck. With REAMACS about one in three or four “crashes” include a POV which is stationary when struck. Reference [10] estimates that 67% of police reported rear-end crashes in the U.S. include stationary POVs. Second, the database is highway data and therefore does not represent vehicle pair characteristics of other roadway types.

Another caveat on the results is that the in-path nuisance alerts studied here are just one type of unnecessary alert. Many types of unnecessary alerts are likely to occur with FCW deployment. Out-of-path nuisance alerts are common in today's systems. For example, an overhead bridge may fool a radar system, or a laser radar system may interpret a roadside sign on a curve as a vehicle. False alarms may also occur for other reasons including as sensor noise or cross-talk with other FCWs. The frequency of these sensor and sensing-interpretation errors may diminish as sensor technology and sensor processing algorithms develop. In-path nuisance alerts are likely to remain, though, since FCWs cannot distinguish between drivers unaware of possible danger and drivers already aware of the situation, and alert timing must always account for the perception-reaction time delay of an inattentive driver. What makes FCW feasible is the fact that vehicles are capable of much higher levels of braking than the discretionary levels of braking used by alert drivers. This makes it possible to delay a warning well beyond the point at which most alert drivers would normally begin to brake.

Major findings include:

1. A target sensor that can support warnings at a 75 meter range provides 94% of the benefits of a sensor with unlimited range. With a more accurate representation of stopped POV situations, however, a longer working range may be beneficial.
2. There is a potential for FCWs to reduce relative harm by up to 67 percent in FCW-equipped vehicles using the cautionary crash alert and an error-free sensor supporting a 75 meter warning range. When used as the only warning, the imminent crash alert has a potential to reduce relative harm by only 20% – this alert occurs too late for much benefit with decelerating POVs.

When lead vehicle information is considered, there is a potential to reduce relative harm up to 81% using a set of algorithm parameters corresponding to both the cautionary and imminent parameters, and a sensor that supports a 75 m warning range.

3. Estimates of the expected exposure of a driver to in-path nuisance alerts are sensitive to modeling assumptions regarding braking levels that drivers are comfortable using in situations they consider non-alarming. Also, in-path nuisance alert rates estimated in this report are likely to be low, since simulation work here assumes all POVs brake to a stop, while in reality many, if not most, nuisances will occur when POVs brake only momentarily. For the cautionary crash alert design considered, a rough scaling analysis estimates that 28 in-path nuisance alerts for every rear-end crash with an impact speed of ten miles per hour or greater. This scales to one in-path nuisance alert per 4.2 years. The imminent crash alert design leads to only 1.3 in-path nuisance alerts per rear-end crash with at least a ten mile per hour impact speed. Future experimental studies are needed to provide more reliable scaling factors to use simulation results to predict real-world experience.
4. Simulation suggests that use of information about POV deceleration by a rear-end collision warning algorithm has the potential to improve FCW performance. This includes a possible increase in the potential reduction in harm as well as an easing of

the need to tradeoff between reducing relative harm and increasing the in-path nuisance alert rate. By adding POV deceleration information to the imminent crash alert, the potential for reduction in relative harm increases from 20% to 81%, however, the corresponding in-path nuisance alert rate increases from 1.3 to 13.5 per rear-end crash with impact speed of ten miles per hour or more. By adding both POV deceleration information and varying the warning algorithm design, a potential reduction in relative harm nearly equal to that of the cautionary crash alert can be achieved. (79%). While the in-path nuisance rate drops from 28 to 2.3 alerts per rear-end collision with impact speed of ten miles per hour or greater.

In practice, in-path nuisance alert rates may be different than reported here for warning algorithms that use lead vehicle deceleration information. There are two reasons. First, this work studies a particular class of such warning algorithms, which is those algorithms that assume the lead vehicle will continue braking at its current deceleration until it stops. The simulated situations, however, match this same scenario – the lead vehicle brakes completely to a stop. In practice, many nuisance alerts will occur for these algorithms when the lead vehicle brakes only momentarily, and so the in-path nuisance rate is likely to be higher in practice for this set of algorithms. Second, warning algorithms can use different assumptions about the future braking levels of the lead vehicle. These other algorithms are not studied here.

5. The simulation results suggest it is possible to define a FCW warning algorithm capable of triggering alerts which are timely enough to significantly reduce rear-end crash harm while not producing so many in-path nuisance alerts that drivers reject the system, nullifying any overall benefit. This conclusion is based on a proposed model that defines alarming situations by the braking levels necessary to avoid a collision. Results of the ongoing human factors experiments portion of this Project will provide a sounder basis for such models, and may affect the conclusion.
6. There is a lack of comprehensive field data on actual vehicle-following and braking behavior. More data is needed to improve confidence in predictions of potential benefits of FCW deployment.

These conclusions are drawn from simulation studies. To map these results into predictions of actual deployment results, the reader must consider the correspondence of the assumptions used in the analyses with actual traffic situations and driver behavior in the real world.

The remainder of the document is as follows. Section C.4 describes the modeling and simulation components. Section C.5 presents the two warning algorithm designs that are studied; three sets of parameters are also introduced. Section C.6 presents results of the potential reduction in relative harm for the two warning algorithms and several sensing ranges. Section C.7 describes a simulation tool that is derived from REAMACS and used to estimate the frequency of in-path nuisance alerts that accompany FCW deployment. That section also contains simulation results for in-path nuisance rates, as well as discussions of the combined harm-reduction and nuisance rate findings. Section C.8 presents a set of studies exploring the sensitivity of the results to the database set and two model parameters. Section C.9 summarizes findings.

C.4 Estimating the Potential Reduction in Relative Harm

A FCW installed on a host “subject vehicle” (SV) should issue warnings if a lead vehicle – the “principal other vehicle” (POV) – is in an “Alert Zone” and is also at a distance less than a specified range. One option for computing this specified range is to use the instantaneous difference in vehicle speeds – the closing speed – and two parameters which can be interpreted as parameters of a model of the expected reaction by a driver to an alert. Another option is to factor in knowledge of lead vehicle deceleration to improve the timeliness. In support of developing minimum functional requirements for FCW systems, the simulation work here estimates the potential for reducing relative harm that is possible for different collision warning algorithms, each with three different parameter sets, as well as sensing ranges of 20 to 300 meters.

Two specific warning algorithms are given names here: an earlier “cautionary crash alert” and a later “imminent crash alert”; the difference between the two alert timings being the numerical values of the two parameters. Both the cautionary crash alert and imminent crash alert are studied in this report, and they are studied separately, as single-alert systems. Four other alert designs are studied as well; more details of the crash warning algorithms and parameter sets are provided in Section C.5. Studying these alerts in a single-alert context is a start, and can make use of the literature on perception-reaction times to single events.

This report does not consider the effects of an adaptive cruise control system on the performance of the FCW. This work is possible, but is outside of the scope of the Project.

The modeling and simulation in this report consists of several components: the FHWA database of vehicle pair headway and speeds; the simulation tool REAMACS; a set of warning algorithms and associated parameter sets and a set of possible sensor ranges; and discussions that address how the simulation results may relate to FCW effectiveness in the real world. These components are addressed in the following sections.

C.4.1 FHWA Database

The vehicle pair database is a FHWA database generated using a pair of loop detectors on Interstate I-40 in Albuquerque, New Mexico. Two days of data were collected, each representing about 35,000 vehicle pairs. The data for each vehicle pair in the database includes each vehicle's speed, time headway, following distance, time interval, time of day, average traffic flow, and the mean speed of vehicles over a relatively long time period. The loop detectors provide no information regarding either vehicle's acceleration. REAMACS does not use time of day, flow, or mean speed. Figure 4 shows the data collected for three vehicle pairs, as an example. The September 25, 1991 data was used for the work in this report; Section 0 looks at the sensitivity of results to using the second day of data (July 11, 1993).

Lane	Veh 1 Speed (mph)	Veh 2 Speed (mph)	Headway (sec)	Follow Distance (ft)	Interval (sec)	Time (hr)	Flow	Mean Speed (mph)
1	98.643	70.765	59.902	4238.978	-27.877	5	8	76.20
1	70.765	73.703	4.433	326.707	2.937	5	8	76.20
1	73.703	70.765	14.005	991.044	-2.937	5	8	76.20

Figure 4 Excerpt from FHWA Database

C.4.2 REAMACS Approach

REAMACS is an acronym for "Rear-end Accident Modeling and Countermeasure Simulation." REAMACS is a quasi-Monte Carlo simulation tool designed to estimate the possible efficacy of rear-end collision warning (FCW) and/or adaptive cruise control (ACC) systems in helping drivers avoid or mitigate rear-end crashes [2][3][4][5][6][7]. For this work and for previously published work with REAMACS, the FHWA database of actual vehicle pair speeds and headways is used to provide initial conditions for generating potential crash scenarios. REAMACS then applies a POV deceleration and a driver reaction to that braking event. Those scenarios which are found to be potential rear-end situations are re-simulated using a countermeasure in parallel with the driver's reaction to the POV braking. Comparison of the outcomes between the driver-alone simulation and the driver-plus-countermeasure simulation provides an estimate on the potential for relative harm reduction. This comparison, in this report, is valid under *ideal* circumstances of countermeasure design and implementation, usage, and driver compliance. The phrase "potential for reduction in harm" in this report carries with it all the assumptions of this ideal setting; these assumptions are stated throughout the report.

The work reported here adds to previous results in the following ways. First, for estimates of potential reduction in harm, this report examines the specific warning properties of several algorithms. This includes warning algorithm parameter sets, which are not considered by earlier REAMACS reports. Second, minor revisions in the code improve the random distribution sampling and add a 1.2 second time delay to the warning algorithm which uses POV deceleration. Third, and most importantly, an approach to estimating the frequency of in-path nuisance alerts has been proposed and used to generate estimates of how often drivers will encounter alerts, especially those they will consider "nuisances," during operations with a FCW-equipped vehicle. This is described in Section C.7.

The potential for reduction in harm that is computed here is based on SVs equipped with FCW systems which always identify appropriate targets, and issue warnings exactly as intended, except for limits on the sensing range and time delays between sensing and computation. Out-of-path effects are not treated here. All vehicle pairs treated consist of two vehicles traveling in the same lane, and the only evasive maneuver treated is braking. No effects of driver compliance changes due to nuisance alerts are included; there is scant literature for modeling how drivers may not accept, not use, or not obey FCW systems.

The models and simulation logic used to compute reduction in harm estimates are generally identical to recent work by Farber and colleagues, with differences noted where appropriate. The first run-through of database vehicle pairs is to generate potential rear-end crash scenarios. When information on a vehicle pair is read from the database, the first step is to reject data that includes very unlikely spacing and relative speeds, such as that resulting from occasional trailer configurations that were not screened out during database generation. Vehicle pair data is rejected if the following distance is less than 4.6m, or if a deceleration of more than 0.30g by the following vehicle is required to avoid a crash, since it is assumed that drivers will not place themselves in such a situation. Of approximately 36,000 vehicle pairs in the September data set, 230 pairs are rejected. To create a sufficiently large pool of potential crashes for the quasi-Monte Carlo approach, the database is cycled through one hundred times, representing over 3.5 million POV braking events. With the parameter sets described below, about four to six hundred potential crash pairs are identified, representing about one potential crash scenario for every 6000 vehicle pairs.

REAMACS, of course, could use other databases, if they were available. Use of a single database based on loop detector data carries with it consequences. The simulation results cannot reflect FCW performance for different roadway or traffic conditions. Since the loop detectors will not record any stopped vehicles, crash scenarios with stopped POVs can only be generated as a byproduct of POVs decelerating within the simulation to a stop. Consequently, the model yields a smaller proportion of crash scenarios with stopped POVs (about one in three or four simulated crashes) than that described by statistical studies of the rear-end crash problem (67%, as reported in [10]). An area of potential follow-on work is the revision of REAMACS to create more cases of stopped POVs. Another consequence of the use of vehicle pairs is that no multiple-vehicle crash scenarios are addressed in this work.

Given valid data from a vehicle pair, the simulation begins a braking deceleration by the POV. The braking level is drawn from a normal distribution of mean $-0.17g$ and standard deviation of $0.10g$, based on field measurements of over 4000 vehicles at 12 sites of discretionary braking [6]. In simulation, this distribution is sampled until a draw between $-0.06g$ and $-0.80g$ is made. In the simulation, the POV continues braking to a stop. (Section C.8.2 looks at the sensitivity of results to POV deceleration levels, as does [3]).

The SV driver's response to the lead car braking; is quantified by the perception reaction time and the braking intensity. Driver reaction time to lead car braking is modeled as a sample from a lognormal distribution with a headway-dependent mean and standard deviation. This model is based on work of Olson [11], which presented subject drivers with a surprise roadway obstacle and measured time until the brake was touched. The lognormal distribution provides a significant "tail" of long response times to model inattentive or distracted drivers. The dependence on headway is intended to model increased alertness for tailgating drivers; this effect is not well understood and is examined in only two studies [12][13]. The mean and standard deviation of the log-normal distribution are assumed to be linearly increasing with headway between 0.5 and 3.0 seconds. The log-mean ranges from $\ln(1.1) = .096$ to $\ln(1.5 \text{ sec}) = .405$ as headway varies from .5 sec to 3 seconds. The log-SD varies from 0.15 to 0.4 over the same headway range. For headways greater than 3 seconds, the distribution parameters do not change, and are directly from [11].

Braking intensity applied by the SV driver is modeled as 0.7g to represent a driver's attempt to avoid a crash by braking hard. A delay of 0.2 seconds is applied between the driver's brake application and a change in the SV deceleration; this represents the dynamics of the braking system. Given the simulated SV driver's response to the lead car braking, the simulation computes whether a rear-end collision occurs. If so, the vehicle pair and its associated randomly sampled POV deceleration level and following driver reaction time to the braking event becomes one member of the crash data set. The impact speed is stored for later comparison with the response of an FCW-aided driver.

Two assumptions are implied by the SV driver model just described. First, it is assumed that the pavement will support a 0.7g braking event – i.e., that for those cases where this level is required, dry pavement is implicitly assumed. Approximately eighty percent of police-reported rear-end collisions occur on dry pavement [14]. Second, the computer simulation assumes that braking is the only countermeasure taken by the driver – the possibility that steering might be used successfully to avoid a crash (either with or without a FCW present) is not addressed.

Once all vehicle pairs in the database have been processed in this fashion, the combinations of vehicle pairs define the potential crash scenarios and random number draws that led to crashes. These cases are used in a second simulation pass, this time with a FCW present. The second pass re-uses the values for the lead car braking level and the SV driver response time to the braking event. Models are added for range sensing and computation of the warning algorithm. Sensing of the range and range rate to the lead car is modeled as ideal, except for an upper bound on the range at which the sensor can help provide warnings, which is varied from 20 to 300 meters. A delay of 0.20 seconds is also associated with the availability of range and range rate data. The simulation assumes perfect identification of appropriate targets. The warning algorithms are described in Section C.5.

In the second pass through the potential crash scenarios, the SV driver may be motivated to brake either by his or her reaction to the lead car braking (as in the first pass), or by an alert from the warning algorithm. Response time to the alert is drawn from a normal distribution with mean and standard deviation of 1.10 and 0.305 seconds, respectively. This follows from [11]. The driver is assumed to brake based on whichever response time finishes first and the same 0.7g braking level is used. If the response to the alert occurs first, then the 0.2 sec braking system is applied again, and the crash may be mitigated or prevented due to the alert. The potential for reduction in harm is the percent decrease in the sum over all crash data sets of the squared impact speed, as described in Section C.3.

C.4.3 Outputs of the REAMACS Tool

To illustrate the outputs of the REAMACS tool, Figure 5 shows the output listing from a single REAMACS run using the closing speed warning algorithm and the cautionary crash alert parameter set. The upper section of the output of Figure 5 reports baseline tallies. These include: the number of vehicle pair scenarios investigated (100 iterations of 35,683 vehicle pairs, or over 3.5 million total pairs); the number of warnings that are triggered by vehicle pair state values as read directly from the database (1600, or 448 per million vehicle pairs); and the number of crashes that occur without a FCW to aid the driver (669, or 187.5 per million vehicle

pairs). The second and third sections provide statistical counts of the number of crashes with and without a FCW; in this example, system ranges of zero (no FCW) to 300m are studied. "Police Crashes" (or "PR" crashes, for "police-reportable") are simulated crashes with a relative impact speed of 4.6m/sec or greater (about 10 mph), since this is roughly the speed at which significant vehicle damage can be expected. For instance, in the last column in the first large table, it is seen that a system with a 100m range reduces "Police" crashes by 51% in the simulation. The bottom table in Figure 5 includes two results of note. First, for each system range, the simulated crashes are sorted into bins reflecting the impact speeds, for example, for a system range of 0m (no FCW), there are 407 crashes with impact speeds of 10 mph or less. Second, the table presents the relative harm computed for each system range. The figure show, for example, that the normalized relative harm for a FCW with a 100m range is 30%, for a potential 70% reduction in relative harm.

The second table in Figure 5 shows that with a system range of zero (no FCW), there are 250 PR crashes, or $250/3.57\text{million} = 70.1$ PR crashes per million REAMACS braking events. An earlier REAMACS paper, Farber and Paley [4], reported 65 PR crashes per million events (the number is slightly larger in this report due to an improved random distribution clipping routine, as described earlier). In [4], Farber and Paley estimate the actual frequency on U.S. roads as between 4 and 40 PR crashes, based on Farber's estimate of one PR rear-end crash per 2.5 million foot-off-throttle events, and one full stop in every 10 or 100 such events. Thus REAMACS generates rear-end crashes at a higher rate than actual traffic by a factor of about 2 to 18, depending on assumptions. Recall, though, that REAMACS is used here primarily to *compare* different warning algorithms and to *approximate* the potential for reducing harm. It does not necessarily provide accurate predictions of absolute performance, such as absolute reductions in crashes.

C.4.4 Regarding Interpretation of Simulation Results

Modeling is by definition a simplified version of reality. Some issues that may be important in real-world reduction in harm are not treated in this work. A few of these are:

- Non-ideal values for deployment and use of FCWs by drivers are not treated.
- The analysis does not treat the possibility that some drivers will not always comply with FCW warnings with prompt braking. (False alarm rates may reduce the drivers reflexive use of brakes to a warning, reducing effectiveness even of timely warnings.)
- No risk compensation effects are treated in this work. (Risk compensation may have a variety of effects on actual benefits.)
- Sensing imperfections by the FCW target sensing system are assumed to include only range limitations and time delay. Errors in identifying and tracking in-path targets are not treated.

Reamac4f - CRA - 0.0 Minimum Headway
08-18-1997 07:49:00

CAMP algorithm, cautionary level -0.3g, 2.5sec

File size = 35683 veh pairs
Number of iterations = 100
Total count = 3568300
Total warnings = 1600
Warnings/million vehicle pairs = 448
Total crashes = 669
Crashes/million vehicle pairs = 187.5
Warnings per crash = 2
Run time = 2006.602

System Range (m)	Total Crashes	Police Crashes		Mean Impact Speed (mph)	Percent Reduction in Crashes	
		Number	Percent		Total	Police
0	669	250	37.4	11.6	0.0	0.0
20	526	218	41.4	12.6	21.4	12.8
50	486	184	37.9	11.2	27.4	26.4
75	442	130	29.4	8.8	33.9	48.0
100	432	122	28.1	8.4	35.6	51.6
150	431	121	28.1	8.4	35.6	51.6
300	431	121	28.1	8.4	35.6	51.6

DeltaV (mph)	System Range (m)						
	000	20	50	75	100	150	300
0 to 10	407	299	293	302	300	300	300
10 to 20	153	120	104	98	96	96	96
20 to 30	54	52	54	36	31	31	31
40 to 50	18	18	6	1	1	0	0
50 to 60	8	8	0	0	0	0	0
60 to 70	0	0	0	0	0	0	0
70 to 80	0	0	0	0	0	0	0
80 to 90	0	0	0	0	0	0	0
Relative Harm	100 %	93%	63%	33%	30%	29%	29%
Potential for Reduction in Relative Harm	0%	7%	37%	66%	70%	71%	71%

Figure 5 Sample REAMACS Output. Closing Speed Algorithm, Cautionary Crash Alert

- Dry pavement is assumed for simulating hard braking to avoid collisions. (Eighty percent of crashes occur on dry pavement [14], but there has been no attempt here to model the reduced braking capability wet pavement can support – this can be expected to reduce the benefit by several percent.)
- The computation of metrics uses braking as the sole countermeasure, although evasive steering action can be more effective in some situations. Studies have shown that drivers are more likely to use braking alone than steering alone [15]. (The effect of this is unknown. On one hand, this assumption may exaggerate the effects of the warnings, as drivers who react late to a rear-end collision situation may avoid a crash by steering, whereas the analyses here assume only braking is available. On the other hand, a FCW may also alert a driver in time to use steering effectively.)
- Driver-interface design effects are not considered. Drivers are assumed to always understand and respond appropriately to alerts.
- Multiple-vehicle rear-end collisions are not studied. Whether the effectiveness of FCWs will be greater or less is not known.

C.5 Warning Algorithms Used in the Analysis

This section presents the two warning algorithms considered in this report, a "closing speed" algorithm, and a "POV deceleration" algorithm. These two algorithms are often used by researchers studying rear-end collision countermeasures. Other algorithms studied by other researchers include warning algorithms based on time-to-collision, algorithms using headway terms, and algorithms using assumptions regarding POV and subject vehicle decelerations that are different than those used in the POV deceleration algorithm described here. These other algorithms are not treated here, but remarks regarding a few of them are offered later in this section.

C.5.1 Warnings Based on Closing Speed

The closing speed warning algorithm in the subject vehicle (SV) issues a warning when the following distance to the lead vehicle, or the "principal other vehicle" (POV), falls below a threshold. The threshold depends on the closing speed, as well as on parameters of a model describing a model of the SV driver's reaction to the alert. Assume the SV driver reacts so that the SV begins a step acceleration of magnitude $a_{sv} < 0$ (negative for braking) at a time RT_w after the alert sounds. Let V_{sv} and V_{pov} denote the speeds of the SV and the POV, respectively.

Consider a warning issued when two conditions are satisfied: (1) the SV is closing on the POV, $V_{sv} > V_{pov}$, and (2) the range R from the SV to the POV becomes equal to or less than a warning threshold, R_w :

Equation (1)

$$\text{Warn when } V_{sv} > V_{pov} \text{ and } R \leq R_w = RT_w \cdot (V_{sv} - V_{pov}) + \frac{(V_{sv} - V_{pov})^2}{-2a_{sv}}$$

The first term in the expression for the threshold R_w is the distance the SV closes on the POV during the design value of the driver's perception-reaction time. The second term is the distance the SV closes on the POV before a deceleration by the SV of design value a_{sv} brings the closing speed to zero. Therefore if the SV and its driver behave exactly as the algorithm design model assumes – i.e., a time RT_w after the alert is issued, an acceleration $a_{sv} < 0$ is applied – then the range and range rate will go to zero at the same instant, and the SV will barely touch the POV. That is, the alert occurs at the last possible instant for the modeled SV and SV driver to avoid a collision. If the actual driver's response is more aggressive than the model assumes, no contact will occur. If the driver's response is less aggressive than the model assumes, an impact occurs, although the impact is likely to be less severe than if no collision warning was issued.

Three parameter sets are studied in this report. Two sets correspond to the "cautionary crash alert" and the "imminent crash alert" requirements. A third set is also studied in this document; this set is called the "intermediate" set, and uses driver reaction parameter values between the cautionary and imminent requirements:

(Equation 2)

$(RT_w, a_{sv}) =$	(2.5 sec, -0.3g)	"cautionary crash alert"
	(1.5 sec, -0.5g)	"imminent crash alert"
	(1.5 sec, -0.3g)	"intermediate"

A major drawback of the closing speed algorithm; is that any deceleration of the POV that occurs between the moment of alert and the time at which the closing speed is brought to zero, violates the assumptions made in deriving the algorithm – any POV deceleration during this period requires a more aggressive driver response than that described by the design parameter set (RT_w, a_{sv}) . Therefore this algorithm requires a design tradeoff between performance in situations of decelerating POVs and situations with constant speed POVs (including the case of a stopped POV). The alert may feel "late" when the POV is decelerating, or an increase of in-path nuisance alerts may result in situations of non-decelerating POVs.

C.5.2 Warnings Using Information on POV Deceleration

The tradeoff that the closing speed algorithm requires between performance with decelerating and non-decelerating vehicles is eased if information regarding the POV's deceleration is available. This information may be gathered by estimation using ranging sensor measurements (e.g., differentiating range rate), through assumptions or inferences of POV deceleration, or received by cooperative means (e.g., from a transponder on the POV). Regardless of the technology, the use of POV deceleration can provide timely alerts with fewer in-path nuisance alerts.

Consider a warning algorithm that uses the same model as before to describe the SV driver's reaction to an alert, but now assumes that POV deceleration, $a_{pov} \leq 0$, is known, and that the POV will continue to decelerate to a stop. Assume also that the SV acceleration between the

moment of the alert and the beginning of the SV driver's deceleration response is zero. A conditional algorithm results, as shown in Equation 3.

Equation (3)

For $a_{pov} = 0$ and $V_{sv} > V_{pov}$:

$$R_w = \frac{(V_{sv} - V_{pov})^2}{-2a_{sv}} + RT_w(V_{sv} - V_{pov})$$

For $a_{pov} = 0$ and $V_{sv} \leq V_{pov}$:

$$R_w = 0$$

For $a_{pov} < 0$:

If $V_{sv} > V_{pov} + a_{pov}RT_w$ and $-\frac{V_{sv}}{a_{sv}} < -\frac{V_{pov}}{a_{pov}} + RT_w$:

$$R_w = \max \left(0, \frac{(V_{sv} - V_{pov} - a_{sv}RT_w)^2}{2(a_{pov} - a_{sv})} + \frac{1}{2}a_{sv}RT_w^2 \right)$$

Else

$$R_w = \max \left(0, \frac{V_{sv}^2}{-2a_{sv}} - \frac{V_{pov}^2}{-2a_{pov}} + V_{sv}RT_w \right)$$

If the POV does indeed maintain constant braking deceleration until it stops, and the SV driver's braking response matches exactly the design model, then again the range and the range rate will both go to zero at the same instant – the SV will barely touch the POV. This can be seen in the equation above. If the first conditional statement applies, the algorithm is identical to the closing rate algorithm. The last two equations for the warning threshold R_w apply if the POV is decelerating; the two equations apply when, respectively, the potential collision would happen while both vehicles are moving, or when the POV has come to rest.

In practice, the potential benefits of using POV deceleration in a warning algorithm may not be fully achieved, due to implementation issues. For example, obtaining POV deceleration may involve differentiating noisy range and/or range-rate information as well as lowpass filtering to remove noise and provide a reliable signal. This adds significant lag, on the order of one to two seconds in some current radar- or laser radar systems. In addition, even if perfect instantaneous knowledge of POV braking deceleration is available, the warning algorithm still cannot predict whether the POV will continue to decelerate, or is simply engaging in a short braking event. The warning algorithm is based on assumptions of the future braking forces; these assumptions will influence the algorithm's performance over the variety of actual driving situations.

C.5.3 Remarks on Warning Algorithms and Parameters

Many warning algorithms studied here have been proposed by researchers. Many algorithms are similar to the two described above in that warnings are issued based on a model of the kinematics of the vehicle pair during and after the time of the alert. Various assumptions may be made regarding information available to the warning algorithm (e.g., acceleration measurements for one or both vehicles), the deceleration profiles before and after the SV driver's response to the alert, and the model of the SV driver's perception-reaction time. At least one algorithm – that based on time-to-collision [16] – is not based on a model of the driver response. Another algorithm *assumes* a POV deceleration value, without direct measurement or estimation. This algorithm [9] attempts to combine the advantages of using POV deceleration information with the simpler hardware and software requirements of the closing speed algorithm. Although there are many variations of warning algorithms, even if time and resources were available, an extensive comparison of these various algorithms may not be justified since there may not be enough data about actual braking behavior to construct a meaningful comparison between similar algorithms.

C.6 Results for Potential Reduction in Relative Harm

The previous sections described the database and models used to estimate the potential reduction in harm. This Section reports simulation results for the two warning algorithms and three sets of warning algorithm parameters presented in the previous section over sensor ranges from 20 to 300 meters. Sensor range is defined as the range limitation of the system, i.e., the range beyond which the system cannot provide warnings. Later in the report a method of estimating in-path nuisance alerts for these same algorithms and conditions is described and results presented (Sections C.7 and C.8.)

Table 1 summarizes the different results for estimating the potential reduction in relative harm for the closing speed algorithm. Each cell of the table represents a single run of REAMACS; the example described in Section C.4.3 appears on the bottom row, under the 100m column. Consider first the effect of sensor range on the potential to reduce relative harm. It is seen that for all three sets of algorithm parameters, there is small additional benefit for systems with a range greater than 75m. With regard to the influence of the warning parameters, the earlier alerts provided by the cautionary parameter set yields a much higher potential than the other two sets. Clearly, the selection of the warning parameters has a strong influence on the potential reduction in harm.

Table 2 presents corresponding results of the reduction in the number of crashes from the same set of simulation runs. The first column shows that there are 70.1 police-reportable (PR) crashes per million REAMACS braking events when no FCW is present. For the 100m Alert Zone extent, the second column of Table 2 shows corresponding numbers with the FCW simulated. The third column shows that the effect of the FCW on the number of PR crashes depends strongly on the parameter set – the cautionary set provides a 51% reduction in the number of PR crashes, while the imminent set provides only a 5% reduction. Note that a 0.5% increase in non-PR crashes occurs with the imminent crash alert – this is not a cause for concern, since though many non-PR crashes are eliminated with the FCW, many crashes which were PR crashes become non-PR crashes with the introduction of the FCW. Note, too, that the values for

reduction in relative harm reported in Table 1 are generally greater than the values for reduction in crashes reported in Table 2. The harm metric measures effects of eliminating crashes *and* mitigating crashes. The harm metric also reflects that it is more important to reduce the impact speed in a severe crash than to eliminate a minor crash.

Table 1 Potential Reduction in Relative Harm for Closing Speed Warning Algorithm

	Potential for Reduction in Relative Harm (Versus Cases with Crash Potential)					
	Maximum Warning Range					
Warning Algorithm Parameter Values:	20m	50m	75m	100m	150m	300m
-0.5g, 1.5sec Imminent	2%	18%	20%	20%	20%	20%
-0.3g, 1.5sec Intermediate	3%	27%	42%	44%	45%	45%
-0.3g, 2.5sec Cautionary	7%	37%	67%	70% (see Fig 4)	71%	71%

Note: Each run consists of 100 iterations through the entire database.

Now consider the warning algorithm that uses POV deceleration information, Equation 3 in Section C.5. Table 3 and Table 4 present simulation results for the potential for reduction in relative harm and the possible reduction in the number of crashes. In Table 3, notice that the benefit of the FCW increases significantly up to about ranges of 75m or 100m. For the cautionary set, there is a 90% potential for reduction in relative harm with a 100m system, and Table 4 shows that 87% of PR crashes are avoided with the FCW in these experiments. In fact, for all algorithms considered a system range of 75m gives at least 94% of the total potential possible with an unlimited (300m) range. One caveat, however since REAMACS and the database that is used combine to under-represent the situation in which a POV is stopped at collision time. The 75m value described here, as being the “knee” of the curve may be lower than the range found if POV -stopped cases were properly represented.

It should also be noted that the difference in the reduction in relative harm numbers is smaller between the parameter sets than it was for the closing rate algorithm. This is because the use of any of the three-parameter sets provides a quite effective FCW for these simulated situations. As stated in Section C.5; after the initial 1.2-second time delay in the simulated algorithm, the FCW “knows” exactly the kinematics of the situation, and since the “drivers” comply perfectly, crashes can only happen when either the reaction times drawn exceed the design times of 1.5 or 2.5 seconds, or when the time delay of the FCW impacts its effectiveness (which is not often, in these simulations).

**Table 2 Reduction in Number of Crashes: Closing Speed Warning Algorithm.
100m Alert Zone Extent**

	No FCW	With FCW	Percent Change with FCW
PR crashes (impact speed > 4.6m/sec), per Million REAMACS braking events			
Imminent 1.5sec RT, -0.5g	70.1	66.4	-5.2%
Intermediate 1.5sec RT, -0.3g	“	58.0	-17%
Cautionary 2.5sec RT -0.3g	“	34.2	-51%
Non - PR crashes (impact speed < 4.6m/sec):			
Imminent 1.5sec RT, -0.5g	117	118	+0.5%
Intermediate 1.5sec RT, -0.3g	“	116	-1.2%
Cautionary 2.5sec RT -0.3g	“	86.9	-26%
All Crashes			
Imminent 1.5sec RT, -0.5g	187	184	-1.6%
Intermediate 1.5sec RT, -0.3g	“	174	-7.2%
Cautionary 2.5sec RT -0.3g	“	121	-35%

Table 3 Potential Reduction in Relative Harm for Warning Using POV Deceleration Estimates (Delay in Getting POV Deceleration = 1.2 sec.)

	Potential for Reduction in Relative Harm (Versus Cases with Crash Potential)					
	Max Warning Range					
Warning Algorithm Parameter Values:	20m	50m	75m	100m	150m	300m
-0.5g, 1.5sec Imminent	3%	36%	81%	85%	87%	87%
-0.3g, 1.5sec Intermediate	3%	37%	81%	86%	87%	87%
-0.3g, 2.5sec Cautionary	7%	41%	85%	90%	91%	91%

Table 4 Potential Reduction in Crashes: Warning Using POV Deceleration Estimates – 100m Alert Zone Extent

	No FCW	With FCW	Percent Change with FCW
PR Crashes (Impact Speed > 4.6m/Sec), per Million REAMACS Braking Events			
Imminent 1.5sec RT, -0.5g	70.1	14.3	-80%
Intermediate 1.5sec RT, -0.3g	“	13.5	-81%
Cautionary 2.5sec RT -0.3g	“	9.25	-87%
Non- PR Crashes (Impact Speed < 4.6m/sec):			
Imminent 1.5sec RT, -0.5g	117	106	-9.3%
Intermediate 1.5sec RT, -0.3g	“	103	-13%
Cautionary 2.5sec RT -0.3g	“	74.8	-36%
All Crashes			
Imminent 1.5sec RT, -0.5g	187	121	-36%
Intermediate 1.5sec RT, -0.3g	“	116	-38%
Cautionary 2.5sec RT -0.3g	“	84.1	-55%

Comparing Table 3 to Table 1, it is seen that the potential for reducing relative harm is significantly higher for the warning algorithm that uses POV deceleration than for the closing speed algorithm. This is because the alert is an “earlier” alert for the same parameter set. That is, for a given scenario of POV braking, an alert that uses POV deceleration will almost always occur before an alert based only on closing rate. In fact in a 100m range system, the potential reduction in harm is larger for the POV deceleration algorithm using the “imminent” parameters (85%) than the closing speed algorithm using the cautionary parameters (70%). It is clear that the additional information of POV deceleration may be very useful for a warning algorithm. However, it must be noted that this algorithm assumes that the POV will brake all the way to a stop and thus may be more likely to produce nuisance alarms under a given set of conditions than the closing speed algorithm.

C.7 Estimating In-Path Nuisance Alerts

A new simulation tool was created to compute in-path nuisance alerts, using the same database and scenarios used in REAMACS. This has been named In-Path Nuisance Alert Code (IPNAC). This section describes the modeling of in-path nuisance alerts, and presents results for the same conditions as those addressed for REAMACS in the previous section.

C.7.1 Definition

For this early study, in-path nuisance alerts are defined as follows. An in-path nuisance alert is any alert which occurs in a situation in which the driver – reacting either to the POV braking event itself or to the alert – can brake with his or her “normal” braking intensity and avoid a collision. We assume for now that application of the brakes suppresses a rear-end collision alert, so that if the driver touches the brake pedal in response to his or her perception of the POV braking before the alert sounds, then the alert will not sound during that braking event.

This definition of in-path nuisance alert allows two ways for a nuisance alert to occur during a braking-to-POV -deceleration event. In the first, the driver perceives the need to brake, but before he or she touches the brake pedal, the alert sounds; furthermore, a collision is avoided using only “normal” braking. In the second case, the alert sounds before the driver either notices the situation or before he or she has decided to brake, but nevertheless, the collision is avoided using only “normal” braking. The next subsection clarifies the definition by posing a comprehensive framework into which all alerts that occur with the REAMACS approach can be categorized.

In-path nuisance alerts are very likely with FCWs because warning systems cannot distinguish between drivers who are aware of the traffic situation and drivers who are not aware, due to inattentiveness, distraction, or other reasons. The alert must occur soon enough, to allow for the unaware driver’s perception-reaction time to an alert. Thus the FCW will occasionally annoy those drivers who are aware of the situation and do not consider themselves in danger. Because vehicles are capable of much higher levels of braking than the discretionary levels of braking normally used by alert drivers, it is possible to delay a warning well beyond the point at which most alert drivers would normally begin to brake. Because of the need to allow for a continuously decelerating POV, the algorithm may give a warning at a time that will allow a

crash to be avoided with moderate braking. Such alarms are likely to be regarded as nuisances by alert drivers. A practical algorithm design will seek- to minimize these instances by delaying alerts as long as possible, while still allowing enough time for an inattentive driver to respond safely. It is believed unlikely that the in-path nuisances will be completely eliminated, and those that do occur may affect the driver acceptance, system usage, and compliance with non-nuisance alerts. This report does not include an attempt to estimate this effect. The analysis here is restricted to the estimation of in-path nuisance alerts that may accompany the algorithms. We anticipate that further work will be necessary to estimate the effects of nuisance alarms on realizable harm reduction.

C.7.2 Partitioning Warning Alerts

In the REAMACS scenario, the POV of a vehicle pair begins braking at a randomly chosen discretionary braking level, and continues to brake to a stop. The SV is assumed to be in the same lane as the POV, so that it too must brake to a stop if a rear-end crash is to be avoided. Recall that only braking is considered as a crash avoidance response, and steering maneuvers are not treated. Here a partitioning of the set of all alerts that may occur in braking-to-POV-deceleration events is described. Alerts are partitioned into three categories: “beneficial” alerts, in-path nuisance alerts, and alerts which are neither. Alerts are partitioned based on three factors:

1. When the alert occurs, with respect to the onset of lead car braking.
2. What causes the following car driver to begin braking (the onset of lead car braking or the alert).
3. The level of braking needed to avoid a collision.

First, consider only factors (1) and (2). Three cases are used to describe when an alert occurs during a braking-to-POV event, and what causes the driver to brake during that event. Let Case 1 describe REAMACS events in which the driver brakes due to his or her perception of POV braking, and braking is soon enough so that the alert is suppressed. (It is assumed that brake pedal application suppresses any un-issued alert.) The timeline at the top of Figure 6 describes this case. In the figure, the driver’s reaction time to lead car braking is completed before the alert sounds.

Consider a second situation, Case 2, in which the alert sounds just before the brake pedal is applied, but braking is due to the driver’s own detection of lead car braking. This is illustrated in the center box of Figure 6. Finally consider Case 3, in which the alert sounds before the driver has perceived the need to brake and therefore provides the stimulus for brake application. This is shown in the bottom box of Figure 6.

The third factor listed above is the amount of braking intensity necessary to avoid an impact. Two generic levels of braking are suggested for purposes of partitioning the alerts. Let braking levels be described as “Normal (or less)” and “Hard” braking. The corresponding deceleration rates will be specified later in the report. With the three cases of alert timing and braking stimuli described in the previous paragraphs and the two levels of braking suggested here, a partitioning

of alerts into six subsets is now proposed and illustrated in Table 5. The three cases of alert timing and braking stimulation define the three columns in Table 5; the two braking levels define two rows. The six cells are now discussed.

The first column of Table 5 denotes braking events in which the driver brakes before the alert sounds; for now, the braking level is irrelevant, since the immediate objective is to estimate in-path nuisance alerts. The second column of Table 5 corresponds to Case 2 above – i.e., situations in which the driver perceives the need to brake, but before the brake pedal can be applied, the alert sounds. In this case, it is suggested that if the driver can avoid impact using only normal braking, he or she will consider the alert a nuisance. This is shown in Table 5. If, however, “Hard” braking is required, drivers may not consider the alert a nuisance – perhaps some may welcome the alert as an indication that the FCW was ready to assist them. Finally, for Case 3, which denotes situations in which the alert causes the driver to brake, it seems obvious that when “Hard” braking is required, drivers will generally perceive the alert as “helpful,” since a crash may be averted or mitigated by the alert. If “Normal” braking is sufficient to avoid a crash, the driver is assumed to consider the alert a nuisance, and this is indicated in Table 5.

Table 5 Partitioning Alerts into Six Cells

Braking Level Required to Avoid Crash	Timing of FCW Alert and Cause of Subject Vehicle Braking		
	Case 1	Case 2	Case 3
	No FCW Alert. Braking is due to driver reaction to POV braking. Braking suppresses FCW alert.	FCW Alert occurs, but Braking is due to driver reaction to POV braking. Braking occurs after alert, but before RT to alert.	FCW Alert occurs. Braking is due to driver reaction to alert.
Normal (or less)	No In-Path Nuisance Alert	In-Path Nuisance alert	In-Path Nuisance alert
Hard	No In-Path Nuisance Alert	<u>Not</u> an in-path Nuisance. (Event validates alarm for driver)	<u>Not</u> an In-Path Nuisance. (Alert mitigates/prevents crash)

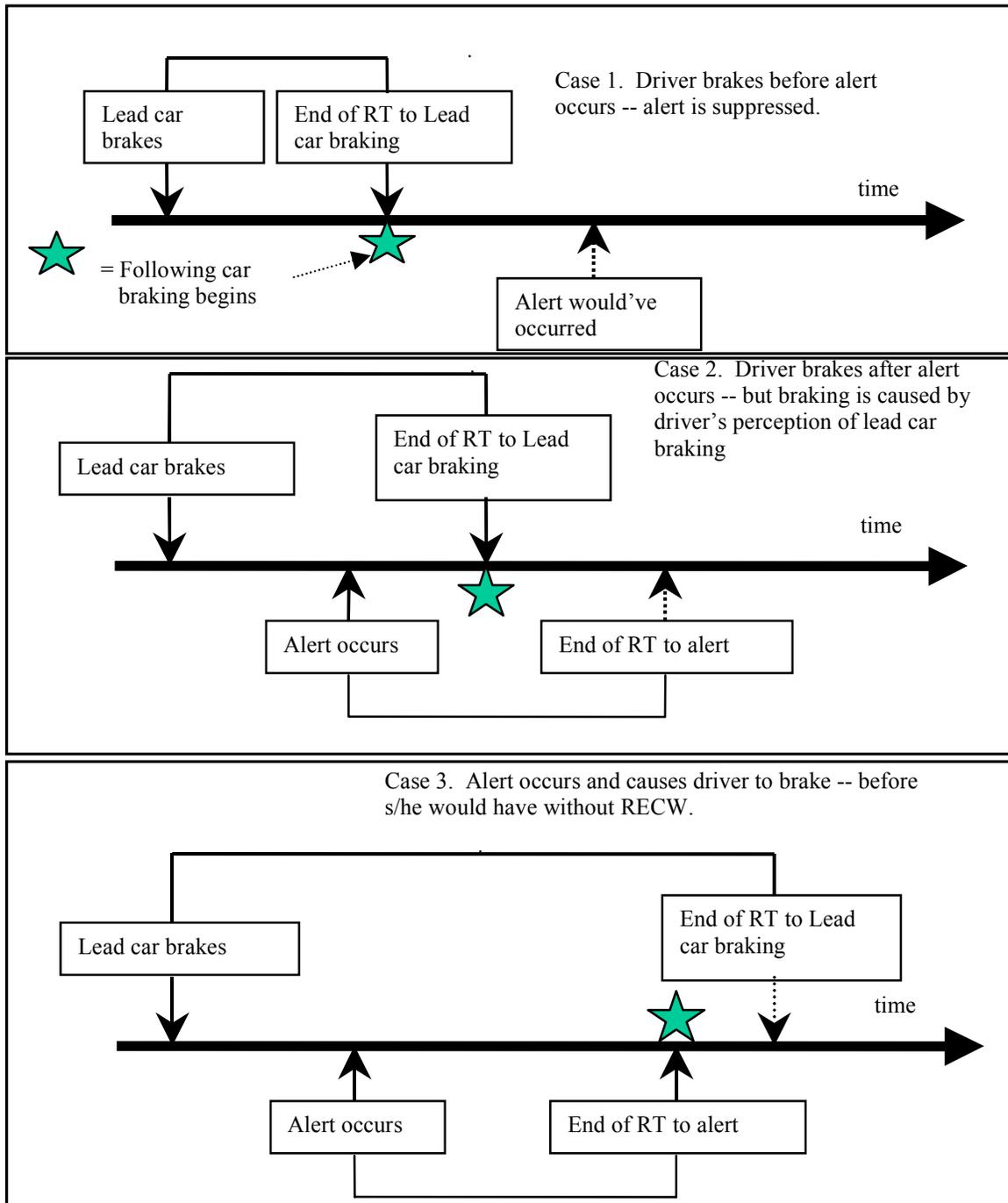


Figure 6 Three Cases of When Alerts May Occur and the Corresponding Stimuli for Braking

C.7.3 Simulation Logic

Here we describe a method to estimate the in-path nuisance alert rate. To estimate the frequency of in-path nuisance alerts, the simulation tool IPNAC uses the FHWA database in the same manner, as does REAMACS. In IPNAC, for each vehicle pair, the following car driver brakes in response to either the lead car braking (using the same driver reaction time to braking model as before) or the collision alert (using the same driver reaction time to an alert, as before). The stimulus for braking is the event for which the driver's reaction time is completed first. No matter the stimulus, a "Normal" braking intensity is selected for the following car deceleration. If an alert occurs and the collision is avoided, then according to the previous definition of an in-path nuisance alert, that simulated case represents an occurrence of an in-path nuisance alert.

The model of the "normal" following car braking is a random sample drawn from a normal random variable distribution with a mean of $-0.25g$ and a standard deviation of $0.025g$. These values are chosen based on a very small sample of Task 4, Study 1 data. This is the average and standard deviation of the first six subjects' required decelerations to avoid a collision when making last-moment braking decisions at "comfortable" braking levels. Values outside the domain $[-0.12g, -0.40g]$ are re-drawn; values outside this domain are assumed to be beyond normal, comfortable braking. Later in this report, the sensitivity of computed nuisance rates to these model parameters is explored. Once the SV begins to brake, the simulation is allowed to play out until either a collision occurs or does not occur. The results of each simulated braking event is then tabulated in a table like Table 5 described earlier.

To describe how simulation is used to evaluate in-path nuisance alerts, consider a single simulation study. The closing speed warning algorithm (Equation 1) is used with the cautionary settings (Equation 2), and an Alert Zone extent of 100m. In-path nuisance alerts are tallied for two to twenty cycles through the database, representing between 70,000 and 700,000 events of braking to a POV. The number of passes through the database is found by trial and error for each algorithm/parameter/range case, by running three Monte Carlos, and using each run for the number of cycles through the database required, so that the variation among the three runs is about five percent or less.

The averaged results are tabulated in Table 6 using the form of Table 5. The first column of the table shows that about 98% of the braking events for this example do not include a triggering of the alert – which is consistent with the fact that drivers almost always avoid rear-end collisions. The second column indicates that in 1.8% of the simulated cases the alert occurs but braking is due to the driver's own perception of the situation. Of these, 1,804 alerts per million events occur in situations where "normal" braking is sufficient to avoid an impact. These are in-path nuisances, as discussed in the previous subsection. The remaining 16,253 events in the second column represent cases in which "Normal" braking is not sufficient to avoid a collision. These cases then require at least "Hard" braking, so that these cases represent drivers braking harder than normal, based on their own perception of lead car braking, but with the alert sounding shortly before they can touch the brake pedal. Our assumption is that these would not be regarded as nuisances, but would be perceived as justifiable alerts.

Table 6 Example of Partitioning Alerts. Closing Speed Warning Algorithm, Cautionary Settings. Perfect Sensing with Alert Zone Limited to 100m

Braking Level Required to Avoid Crash	Timing of FCW Alert, and Cause of Subject Vehicle Braking		
	No FCW Alert. Braking is due to driver reaction to POV braking. Braking suppresses FCW alert.	FCW Alert occurs, but Braking is due to driver reaction to POV braking. Braking occurs after alert, but before RT to alert.	FCW Alert occurs. Braking is due to driver reaction to alert.
Normal (or less) (-0.25g mean)	819,993 alerts per 10 ⁶ braking events	1,804 alerts per 10 ⁶ braking events	6 alerts per 10 ⁶ braking events
Hard	161,767 alerts per 10 ⁶ braking events	16,253 alerts per 10 ⁶ braking events	176 alerts per 10 ⁶ braking events

The third column of Table 6 describes events in which the alert triggers the driver's braking; these total 182 per million simulations. Of these, there are six in-path nuisance alerts and there are 176 cases in which the alert causes the driver to brake in a situation in which higher-than-normal braking intensity is required to avoid an impact. These latter cases may be perceived by the driver as beneficial alerts, i.e., not in-path nuisance alerts.

For this case, Table 7 summarizes simulation results for potential for reduction in relative harm and in-path nuisance alerts. The first four rows were reported earlier: 51% reduction in PR crashes (from 70 to 36 per million REAMACS events), and 70% potential for reduction in relative harm. There are also 1,810 in-path nuisance alerts per million REAMACS events, 182 instances of alerts stimulating the braking, and 18,239 total alerts. *Thus, about 90% of all alerts for this example are neither nuisances nor beneficial alerts.* Instead, these alerts occur while the driver is in the process of responding to their own perception of the need to brake. Table 7 shows that there are 26 nuisance alerts per PR crash without the FCW. When all alerts are considered, there are 261 alerts per PR crash. These ratios provide a rough idea of how often in-path nuisances occur.

Table 8 shows corresponding results for a warning algorithm that uses POV deceleration information (Equation 3) with the cautionary parameter set (Equation 2). About 63,000 in-path nuisance alerts occur, with 5,161 alerts that stimulate braking, and there total of 125,000 total alerts. There are 901 in-path nuisance alerts per PR crash, and 1781 total alerts per PR crash. This alert is an "earlier" alert, hence a higher number of total alerts and in-path nuisance alerts. The ratio of nuisance alerts to alerts is lower, however, possibly because the algorithm can identify the cases in which the POV is decelerating hard, which are often dangerous cases.

C.7.4 Basic Simulation Results for In-Path Nuisance Alerts

Simulation results for in-path nuisance alerts are now presented for the same set of warning algorithms, algorithm parameters, and sensor ranges as reported earlier for potential reduction in relative harm. Table 9 shows in-path nuisance alerts per million REAMACS braking events for the closing speed algorithm (Equation 1), over the three parameter sets already defined (Equation 2), and for sensor ranges from 20 to 300m. These cases are the same as those studied for potential reduction in relative harm, Table 1 and Table 2. The example described in the previous section appears in the shaded cell of Table 9. Table 10 show results for the warnings issued using POV deceleration information (Equation 3); these cases are the same as those studied in Table 3 and Table 4. The example described in the previous section appears in the shaded cell of Table 10.

For Table 9, which shows results for the closing speed algorithm, two results are worth noting. First, in-path nuisance alerts rates are independent of sensor range for the cases studied using the closing speed algorithm. Second, in-path nuisance alerts rates are strongly dependent on the parameter set. As the alert becomes an “earlier” alert, more in-path nuisances occur. For instance, for an Alert Zone extending 100m, Table 9 shows 79.3 and 1,810 in-path nuisance alerts per Million REAMACS braking events for the imminent and cautionary settings, respectively. Since there are 70.1 PR crashes per Million REAMACS braking events, the ratio of these nuisances to PR crashes varies from about 1 to 26.

Table 10 shows the results for the warning algorithm with POV deceleration information included. Three remarks are in order. First, nuisances now increase with an increase of the Alert Zone’s maximum range for the intermediate and cautionary parameter sets. Second, there is again a strong increase in the nuisance rate as the algorithm parameter set results in earlier and earlier alerts. Third, the number of nuisances becomes very large for these earlier alerts – for the cautionary parameter setting, with a 100m extent, 63,100 in-path nuisances occur per million experiments, or 901 in-path nuisance alerts per PR crash. This is 35 times the in-path nuisance rate seen with the closing speed algorithm. On the other hand, the imminent parameter set with the lead vehicle deceleration algorithm produces fewer nuisance alarms and a larger reduction in relative harm than the closing speed algorithm with the cautionary parameter set (see Table 1 and Table 2). This result is discussed further in the next section.

Table 7 Summary: Potential Reduction in Relative Harm and Accompanying Alert Results. Closing Speed Warning Algorithm with Cautionary Setting. Alert Zone Extent 100m

Percent reduction in PR crashes	51 percent
Reduction in Relative harm	70 percent
PR crashes without FCW	70 per Million REAMACS events
Reduction in PR crashes	36 per Million REAMACS events
In-path Nuisance Alerts introduced	1,810 per Million REAMACS events
Alerts stimulating braking at any level	182 per Million REAMACS events
Total number of Alerts	18,239 per Million REAMACS events
In-path Nuisance Alerts per PR crash	26
Total number of Alerts per PR crash	261

Table 8 Summary: Potential Reduction in Relative Harm and Accompanying Alert Results. Warning Algorithm with POV Deceleration Information, with Cautionary Setting. Alert Zone Extent 100m

Percent reduction in PR crashes	87 percent
Reduction in Relative harm	90 percent
PR crashes without FCW	70 per million REAMACS events
Reduction in PR crashes	61 per million REAMACS events
In-path Nuisance Alerts introduced	63,056 per million REAMACS events
Alerts stimulating braking at any level	5,161 per million REAMACS events
Total number of Alerts	124,655 per million REAMACS events
In-path Nuisance Alerts per PR crash	901
Total number of Alerts per PR crash	1781

Table 9 Closing Speed Algorithm: In-Path Nuisance Alerts per Million Simulated Braking Events (Mean of individual Monte Carlo Trials)

	In-Path Nuisance Alerts per Million Simulated Braking Events					
	Maximum Warning Range					
Warning algorithm parameter values:	20m	50m	75m	100m	150m	300m
-0.5g, 1.5sec Imminent	88.3	89.6	89.2	79.3	82.2	75.4
-0.3g, 1.5sec Intermediate	201	200	198	187	181	195
-0.3g, 2.5sec Cautionary	1,810	1,910	1,950	1,810	1,830	1,780

Table 10 Warnings Using POV Deceleration: In-Path Nuisance Alerts per Million Simulated Braking Events (Mean of Individual Monte Carlo Trials)

	In-Path Nuisance Alerts per Million Simulated Braking Events					
	Maximum Warning Range					
Warning algorithm parameter values:	20m	50m	75m	100m	150m	300m
-0.5g, 1.5sec Imminent	833	897	948	943	1,020	922
-0.3g, 1.5sec Intermediate	3,650	14,700	19,600	21,700	22,900	22,900
-0.3g, 2.5sec Cautionary	8,250	38,000	54,400	63,100	67,800	67,900

C.7.5 Balancing Potential Reduction in Relative Harm and In-Path Nuisance Alerts

Examination of the two tables just discussed indicates the possibility of finding an algorithm to produce a high potential reduction in relative harm and also keep the in-path nuisance alert rate relatively low. A simulation study was conducted to compute relative harm reduction and nuisance rates using POV deceleration and a variety of parameter sets that describe warning algorithm design models of “fast and firm” driver responses. These results appear in Tables 11 and 12. Consider an algorithm using a model for the driver’s response to the alert as including a 1.25 second perception-reaction time and a braking intensity of $-0.6g$. The tables show a 79% potential for reduction in relative harm and 161 in-path nuisances per million REAMACS braking events, demonstrating that such a search for a more “optimal” algorithm may be useful. The point is not that this algorithm is considered “best,” but rather to clarify that POV deceleration information allows more flexibility in tuning the algorithm, and that the apparently-higher nuisance alert rates in Section C.7.4 cannot be considered a reason to not use POV deceleration.

Table 11 Potential for Reduction in Relative Harm for Various Warning Algorithm Parameter Sets. Warnings Issued Using POV Deceleration Information. 100m Alert Zone Range Assumed.

asv, Parameter for Warning Algorithm	RTw, Parameter For Warning Algorithm (Blank cells indicate computations were not made for that case)			
	1.0 sec	1.25 sec	1.5 sec	2.5 sec
-0.3g			86%	90%
-0.5g	75%		85%	
-0.6g		79%		
-0.7g	41%		79%	

Table 12 In-Path Nuisance Alerts per Million REAMACS Braking Events, for Various Warning Algorithm Parameter Sets. Warnings Issued Using POV Deceleration Information. 100m Alert Zone Range Assumed.

asv, Parameter For Warning Algorithm	RTw, Parameter for Warning Algorithm (Blank cells indicate computations were not made for that case.)			
	1.0 sec	1.25 sec	1.5 sec	2.5 sec
-0.3g			21,700	63,100
-0.5g	61		943	
-0.6g		161		
-0.7g	12		301	

C.7.6 Metrics to Describe Frequency of In-Path Nuisance Alerts

So far the in-path nuisance alert results have been used to make comparisons between sensor ranges and alert algorithms, and thus the use of the unit “alerts per Million REAMACS events” has been sufficient. To express the simulation results as the frequency that such alerts occur per unit driving time, two simple approaches are used. First, the REAMACS database and braking scenarios are “calibrated” to real-world crash data to map “Million REAMACS events” to miles traveled.

Exposure to Police-Reported Rear-End Crashes

Reference [10] analyzes crash involvements using data primarily from the 1989-93 GES. For rear-end crashes, Table 4 and Table 5 in [10] state that the rate of vehicle involvement (as a striking vehicle (SV)) in actual police-reported rear-end crashes, per 100 million vehicle miles traveled (VMT) is 44.46 and 21.92 when the POV is stopped and moving, respectively. **This yields a total expected vehicle involvement in real-world police reported rear-end collisions (as the SV) of 66.38 per 100 Million VMT, or once per 1.51 Million VMT.**

The same tables indicate that expected involvement of a driver as the SV driver in a police-reported rear-end crash, over a driver’s career (assumed to be 58 years), is 0.7308 and 0.3603 for POV stopped and POV moving, respectively. Section C.1 shows that these numbers are mislabeled, and they are actually the involvement of drivers of any vehicle involved in police-reported crashes. When only involvement as an SV is considered, the rate of vehicle (or driver) involvement per 58-year long driving career [10] are 0.3321 and 0.1637 for POV stopped and moving, respectively, for a total involvement as SV driver of 0.4958 police-reported rear-end crashes per driving career. Thus, under the assumptions of [10], the expected involvement of a driver, as the driver of the striking vehicle in a police-reported rear-end crash, is once per 117 years.

Correction to Wang et al, 1996: Rear-End Collision Involvement

This section presents a correction to two numbers in Wang et al [10] which describe expected driver involvement in the striking vehicle (SV) in a police-reportable (PR) rear-end collision. These numbers are used in Section C.7.6, “Estimated Exposure to In-Path Nuisance Alerts,” to approximate, for the average driver, the time and mileage driven between in-path nuisance alerts. The present authors have discovered no other necessary corrections to [10].

Table 4 and Table 5 in [10] present statistics on two types of rear-end collision, respectively: rear-end, lead vehicle stopped (RE-LVS) crashes and rear-end, lead vehicle moving (RE-LVM) crashes. Among the statistics within each of the two tables is “Expected Involvement as SV in PR crashes – Per Driver over Driver Career”. This is given for all vehicles combined; no breakdown between vehicle types is provided. For the RE-LVS and RE-LVM cases,

respectively, reference [10] states the exposures as 0.7308 and 0.3603, which we will show is incorrect. The correct numbers are, respectively, are 0.3321 and 0.1637.

The miscalculation in [10] appears to be that exposures are computed for driver involvement in *any* vehicle involved in a PR rear-end, and not just in the SV. The reference states the formula used (p. 7, [10]):

$$\text{Expected number} = \frac{\text{Average annual number of involvements} \times \text{Average driving career (years)}}{\text{Average number of registered drivers}}$$

The average driving career is estimated in [10] as 58 years; the average number (over the five years of statistics) of registered drivers used is not specifically stated, but can be backed out of other exposure rates as 170.1 Million. The average annual number of involvements of *all* vehicles is in RE-LVS crashes is 2.144 Million. The average annual number of involvements as the SV is 0.974 Million. Using the formula above gives the involvements per driver career as 0.7308 and 0.3603, respectively. The involvements for RE-LVM can be computed similarly.

As a check, consider that there were 1.454 million police-reported rear-end crashes annually [10]. Given that there are 170.1 million registered drivers in the U.S. (figure derived from [10]), then the expected number of drivers involved as the SV in a police-reported rear-end crash in a year is $1.454 \text{ M} / 170.1 \text{ M} = 0.00854$ (which is $1/117$).

Estimated Exposure to In-Path Nuisance Alerts

To estimate how often a driver might experience in-path nuisance alerts with a FCW, a scaling of results from simulation to “real world” is now performed. Recall that with no countermeasure in place, REAMACS produced 70.1 “police-reportable” crashes per Million REAMACS events, as reported in Table 2. Let this crash rate be denoted Cr. For the warning algorithm design selected in Section 0 (POV deceleration information available, and alerts based on a driver response model of 1.25 sec RT and $-0.6g$ braking), 161 in-path nuisance alerts per Million REAMACS events were computed. Let this rate be denoted Nr, $Nr = 161 \text{ IPNAs}/10^6$ REAMACS events. We use these two results, along with results from the previous subsection, to estimate the expected exposure of drivers to in-path nuisance alerts.

Let C denote a driver’s expected annual involvement as the driver of the SV in a PR rear-end crashes, computed above, $C = 1/117$ PR crash/driving year. Let N be the estimated number of in-path nuisance alerts experienced annually by a driver. Then $N = Nr (C/Cr)$, or

$$N = \frac{161 \text{ nuisances}}{\text{M REAMACS events}} \times \frac{1 \text{ PR crash} / 117 \text{ years}}{70.1 \text{ PR crashes} / \text{M REAMACS events}}$$

$N = 1$ in - path nuisance alert per 50.9 years .

Similarly, we can compute one in-path nuisance alert per 657,000 vehicle miles traveled. Table 13 shows results computed for two other cases as well – the two warning algorithms with the cautionary parameter setting. These numbers all indicate relatively rare in-path nuisance alerts.

These numbers are rough approximations. These computations assume that REAMACS produces two types of braking-to-POV events in the same proportions as they occur in U.S. traffic; these events are (1) police-reportable crashes (with no FCW in use), and (2) braking events which result in in-path nuisance alerts. This is illustrated in Figure 7. The frequency with which PR crashes occur depends primarily on the following variables: range, POV speed, SV speed, POV braking profile, and following driver reaction time to POV braking. The frequency of in-path nuisance alerts depends on the same variables, plus the warning algorithm and the driver’s reaction time to the warning. If we assume that the REAMACS traffic database represents actual speed and headway behavior of drivers, then the assumption that events (1) and (2) occur in proper proportion. The simulation reduces the assumption that the reaction time distributions in the simulation are correct, and the POV braking profile is correct.

C.7.7 Previous REAMACS-Based Metrics for In-path Nuisance Alerts

Previous REAMACS reports used a different metric to estimate in-path nuisance alert rates [4]. This earlier approach is now described and the results compared to those presented above. The earlier method computes how often the initial conditions of the vehicle pair at time (directly from the database) causes a crash alert. For the cautionary setting of the closing speed algorithm, Figure 5 showed that 448 warnings were issued at time T_0 , per million vehicle pairs, based on the vehicle pair speeds and gaps reported directly from the FHWA database. The reason for using this metric as an indication of in-path nuisance alerts is based on an assumption that in almost all cases, the following driver of the vehicle pair chose to be at that headway, and that furthermore almost all of them were not alarmed. Thus, the argument went, the 448 warnings per million vehicle pairs were almost all unnecessary and would be considered nuisances. Since Figure 5 shows 187.5 crashes per million vehicle pairs, the estimate of in-path nuisance alerts would then be $448 - 187.5 = 260.5$ “nuisance alerts” per million vehicle pairs. This number compares with 1,810 in-path nuisance alerts, per million REAMACS braking events (Table 9) computed with the approach of this report. This larger number is more accurate, since now alerts at times other than the initial conditions are considered. Also note that the previous method of counting nuisance alerts did not address the possibility that some alerts that occur at initial conditions may be in truly alarming situations. The current analysis identifies these cases.

Table 13 Approximate Time- and Miles-Between In-Path Nuisance Alerts

(See assumptions in Section C.7.6)

Warning Algorithm	Parameter Set for Warning	Expected Time Between In-Path Nuisance Alerts	Expected Vehicle Miles Between In-Path Nuisance Alerts
Using POV deceleration	Special 1.25sec RT -0.6g decel	50.9 years	657,000 mi
Using POV deceleration	Cautionary 2.5sec RT -0.3g decel	0.13 years	1,700 mi
Closing speed algorithm	Cautionary 2.5sec RT -0.3g decel	4.53 years	58,500 mi

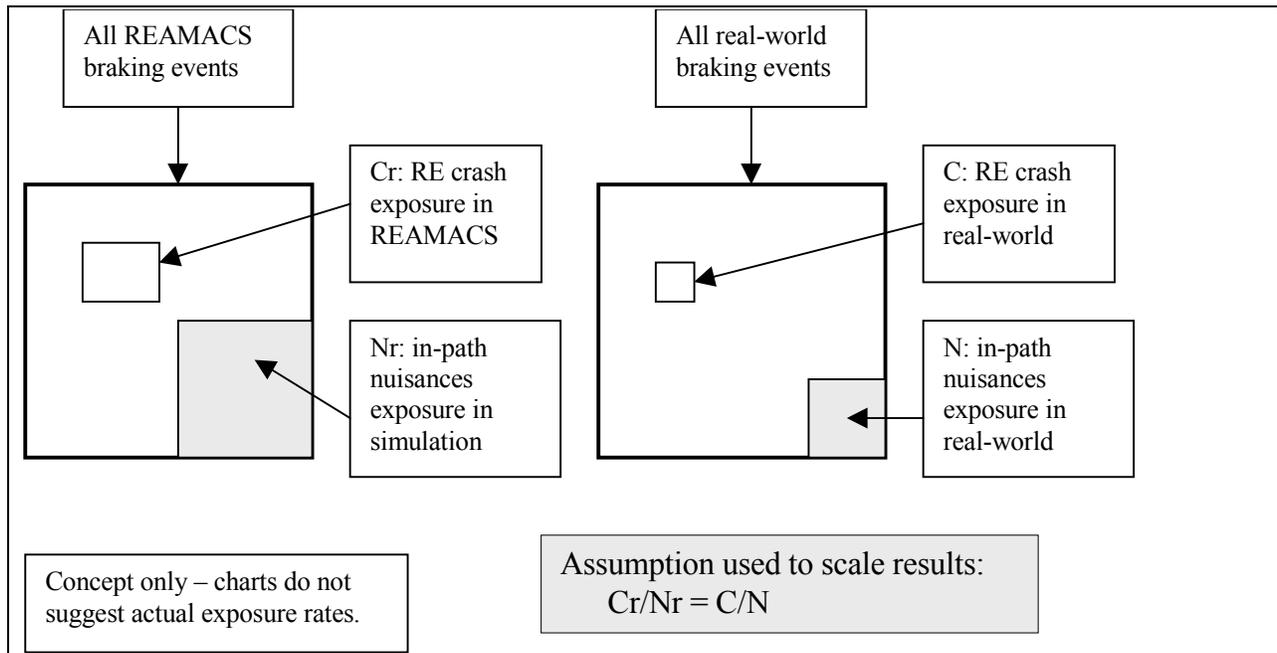


Figure 7 Assumption that the Ratio of Driver Exposures to PR Rear-End Crashes and in-Path Nuisances is the Same in Simulation and Actual U.S. Highway Experience

C.7.8 In-Path Nuisances and Sensor Range Requirements

In Section C.6, an alert range of 75m was suggested, based on the diminishing returns (i.e., potential for reduction in harm) that result from longer ranges. Consider whether the in-path nuisance rates of Table 9 and Table 10 affect this recommendation. First, sensor range does not affect nuisance rates for the closing speed algorithm, so these results have no impact on a sensor range recommendation. Second, it was noted earlier that in-path nuisance alerts increase with sensor range for the algorithm using POV deceleration. These increase by an insignificant amount for the alert resulting from the imminent set of parameters, but more than double for the cautionary set. Section C.7.5, though, argued that with POV deceleration information, a parameter set chosen to give a “late” alert would provide both high potential for reduction in relative harm and a minimal number of in-path nuisance alerts. Therefore, since any alert using POV deceleration information is likely to be such an alert, results reported in this document do not suggest a significant influence on sensor range requirements from in-path nuisance alert rates.

C.8 Sensitivity of Simulation Results to Database and Model Assumptions

In this section the sensitivity of results to three model assumptions is explored. The three assumptions are: expected value of the POV deceleration, expected value of the SV braking intensity, and the assumption that important conclusions are largely independent of the day of database collection. Table 14 summarizes the studies; the following subsections report the work.

Table 14 Sensitivity Studies Performed

Variable	Result To Investigate	
	Potential for Reduction in Relative Harm	In-Path Nuisance Alerts
SV deceleration	No	Yes
POV deceleration	Yes	Yes
Database data: day of collection	Yes	Yes

C.8.1 SV Braking Intensity

In Section C.7, in-path nuisance alerts were defined as alerts occurring in situations in which “normal” braking is sufficient to avoid a collision. Normal braking for that section was described as having an upper limit described by a normal distribution with mean $-0.25g$ and standard deviation $0.025g$. Here the sensitivity to the in-path nuisance rates is examined when both of these model parameters are varied.

When the model is reduced to a fixed, deterministic braking level of $0.25g$ (i.e., the standard deviation is reduced to zero), the results are very similar to the original model. This is shown in the first two columns of Table 15, with the original model values in the second column and the

values corresponding to zero standard deviation appearing in the first column. The six rows of data correspond to the two warning algorithms, each run with all three parameter sets.

Table 15 In-Path Nuisance Alert Rates per Million Braking Events Using Different Braking Intensity Models for the Following Car Driver

	Following Car Braking Intensity Distribution Mean and Std Dev (Normal distribution assumed. Resampled if draws are not between -0.12 and -0.40g)				
	Mean = -.25g Std dev = 0g	Mean = -.25g Std dev = .025g	Mean = -.27g Std dev = .025g	Mean = -.30g Std dev = .025g	Mean = -.35g Std dev = .025g
CAMP Closing Speed Warning Algorithm					
Imminent: 1.5sec RT, -0.5g decel	79.9	79.3	121	214	462
Intermediate: 1.5sec RT, -0.3g decel	185	187	294	490	964
Cautionary: 2.5sec RT, -0.3g decel	1,790	1,810	2,250	3,870	6,576
Warning Algorithm with POV Deceleration Information					
Imminent: 1.5sec RT, -0.5g decel	765	943	1,660	3,480	8,985
Intermediate: 1.5sec RT, -0.3g decel	21,500	21,700	32,700	46,100	61,990
Cautionary: 2.5sec RT, -0.3g decel	65,300	63,100	76,100	91,300	113,397

When the mean of the model is changed to reflect a higher tolerance for braking intensities not associated with threatening situations, the results are shown in the third, fourth, and fifth columns of Table 15. These numbers correspond to model means of $-0.27g$, $-0.30g$, and $-0.35g$. These values are thought to include a likely upper limit of braking considered to be within the realm of non-threatening situations. Reference [6] summarizes results from a 1940 study of braking levels [18] as follows:

Comfortable to passengers—preferred by driver: $-0.27g$.

Undesirable but not alarming to passengers—the driver would rather not use: $-0.34g$.

Severe and uncomfortable to passengers—driver classifies as an emergency stop: $-0.43g$.

Table 15 shows that as drivers view higher braking levels as being non-alarming, the number of in-path nuisances increases, as expected. The increase in the nuisance rate as the model mean changes from $-0.25g$ to $-0.35g$ varies from a five-fold increase for the imminent setting of the closing speed algorithm to a doubling for the cautionary setting of the algorithm which uses POV deceleration information. It is noted that in these braking events, the number of total alerts is not likely to change much. The “drivers” can simply avoid more impacts using only “normal” braking.

The study in this section suggests that if $0.25g$ is nearer the lighter end of what actual drivers consider a non-alarming event, then actual in-path nuisances can be expected to be higher than those reported in this paper, perhaps increasing by several times. Field trials with FCW systems will provide more reliable information. For now, we expect the in-path nuisance rates reported here to be a lower bound on the actual rates that would be experienced with deployed systems on the road.

C.8.2 POV Braking Intensity

REAMACS typically is used with a POV braking model that is a normal random variable with mean $-0.17g$ and standard deviation $0.10g$, as described in Section C.4.2. This section explores the effect on in-path nuisance rates when these POV braking levels are reduced to a mean of $-0.10g$ and standard deviation $0.025g$. The $-0.10g$ rate for POV deceleration was chosen because it may approach the lower bound of actual lead car braking on highways. No higher deceleration rates are studied because it is thought that a mean of $-0.17g$ is near the maximum likely to be typically found on highways. Table 16 shows results for both potential reductions in relative harm and in-path nuisance alerts for both warning algorithms and the cautionary and imminent parameter sets.

First, it is noted that the number of crashes that occur *without* the FCW is reduced dramatically by the lower POV deceleration rate from 70 to 4.4 PR crashes per million REAMACS braking events. This is because more time is available for the SV driver to react to the POV braking event. The level of braking required by the SV also decreases since the POV is not decelerating as hard. Table 16 shows that after lowering the POV braking intensity, the simulation yields an increase in the potential benefits of a FCW.

Table 16 shows also that the in-path nuisances, expressed per unit time (see, in Section C.7.6, “Estimated Exposure to In-Path Nuisance Alerts”), increase as well. The rates are indeed expected to increase, since the following car driver can brake less strenuously and avoid a crash, but the warning logic and settings are unchanged. For the closing speed-warning algorithm with the cautionary parameter setting, in-path nuisances per unit time increase by a factor of 27, from one in 4.5 years to one in two months. Likewise, if warnings include information of POV deceleration, the nuisance rate almost triples, from one in 6.8 weeks to one in 2.5 weeks. Clearly if POVs actually brake so that the mean rate is less than 0.17g, the upper limit on effectiveness will increase, as will the number of nuisance alerts.

Table 16 Sensitivity of Results to POV Deceleration Model: Potential for Reduction in Relative Harm and In-Path Nuisance Alert Rates.

(Cautionary parameter settings (2.5s RT, -0.3g decel))
(100m limit to Alert Zone)

	POV Braking Intensity Distribution Mean and Std Dev (Normal Distribution Assumed. Resampled if Draws are not Between-0.04 and -0.80g)	
	Less Deceleration than Standard Model Mean = -0.100g Std dev = 0.025g	Standard Model Mean = -0.170g Std dev = 0.100g
Potential for Reduction in Relative Harm		
Closing Speed algorithm.	99%	70%
Using Lead Veh Deceleration in warning algorithm	100%	90%
In-Path Nuisance Alerts per Driver-Year (see Section C.7.6 for method of computing)		
Closing Speed algorithm.	5.98 (1 in 2 months)	0.221 (1 in 4.5 years)
Using Lead Veh Deceleration in warning algorithm	21.2 (1 in 2.5 weeks)	7.69 (1 in 6.8 weeks)

C.8.3 Day of Database Collection

Two days of data are discussed – September 25, 1991, which is the data set that results in all other sections of this document are based upon, and July 11, 1993, which we use in this section for comparison. Reference [3] discusses this issue for REAMACS, and we mention those findings in this paragraph. That paper notes that in both days’ data, about a quarter of the headway values are below one second. Traffic was heavier in the September data set, with slower traffic (median speed 54 mph, versus 61 mph for the July set) and smaller median gaps

(1.67 seconds, versus 1.97 seconds for the July set). In that study the July data produced 1/3 more crashes, and PR crashes comprised a higher percentage of the total. Effectiveness was found to be higher with a closing-speed type algorithm for the July data. Potential reduction in relative harm was 77%, versus 63% for the September data set when a 76m (250ft) sensor system was used, and an algorithm quite similar to the closing speed algorithm was used (with a “cautionary” level of parameter values).

In the work reported here, without a FCW in place, the September set results in 70 PR crashes per million REAMACS event, as reported earlier, and the July data set results in 112 PR crashes per million REAMACS events, an increase of 58%. The July data set also yields a higher mean impact speed, too: 13.7 mph versus 11.9 mph. Table 17 and Table 18 present simulation results for both days of the FHWA database. Again, the two warning algorithms studied in this paper are used, and for each algorithm, both the cautionary and imminent parameter sets are used. A 100m Alert Zone extent is assumed. The first column of each table presents the September data set results, which have already been presented and discussed in this report. The second column includes corresponding July data set results.

Table 18 presents potential reduction in relative harm results from REAMACS. First notice the results for the closing speed algorithm – those numbers in the first two rows of numerical values. With the closing speed algorithm, a significantly higher reduction in relative harm is found to be potentially available (assuming ideal compliance, etc.) for the July data set. This result is quite similar to that described in [3] and stated in the paragraph above, however there is a surprise in the second set of results in Table 17. While the potential for reduction in relative harm with the algorithm using POV deceleration and the cautionary parameters are used again is larger for the July data set than for the original September data set, when the imminent parameters are used, the opposite is true. A possible reason for the decrease in the estimated potential for reduction in relative harm with the imminent settings is that the July data set leads to generally higher impact speeds. Thus the imminent setting, which is a “later” alert, may not fare as well as the earlier cautionary alert in mitigating crashes in these scenarios.

Table 18 presents in-path nuisance results for the two days of database collection. The number of nuisance alerts decreases across the board when the July data set is used. This is consistent with the July data set having less tight headway and containing higher delta-velocities – braking events are likely to need more braking to avoid a crash.

So what conclusions can be drawn by comparing the two data sets? When both nuisances and the potential for reduction in relative harm are considered, the July data set yields results that the surface would argue more strongly for FCW development than the September data set: the potential for reduction in relative harm is estimated to be larger, and the number of in-path nuisances is predicted to be smaller. And yet it is the same highway. The real lesson, perhaps, is that the numbers *per se* depend upon the data set used, and so the specific quantitative results in this document should be used with great caution. Also, of course, it is desirable to obtain more data sets with a greater diversity of characteristics before using REAMACS to make fine distinctions between algorithms or parameter sets.

Table 17 Sensitivity of Results to Date of Traffic Data Collection: Potential for Reduction in Relative harm and In-Path Nuisance Alert Rates per Million Braking Events.

(100m limit to Alert Zone.)

	Date of Traffic Data Collection in FHWA Database	
	Sept 25, 1991 (This data used for all other studies)	July 11, 1993 (This data used only for this column in this table)
Camp Closing Speed Warning Algorithm		
Imminent: 1.5sec RT, -0.5g decel	20%	34%
Cautionary: 2.5sec RT, -0.3g decel	70%	80%
Warning Algorithm with POV Deceleration Information		
Imminent: 1.5sec RT, -0.5g decel	85%	80%
Cautionary: 2.5sec RT, -0.3g decel	90%	97%

Table 18 Sensitivity of Results to Date of Traffic Data Collection: In-Path Nuisance Alert Rates per Million Braking Events.

(100m limit to Alert Zone.)

	Date of Traffic Data Collection in FHWA Database	
	Sept 25, 1991 (This data used for all other studies)	July 11, 1993 (This data used only for this column in this table)
CAMP Closing Speed Warning Algorithm		
Imminent: 1.5sec RT, -0.5g decel	79	38
Cautionary: 2.5sec RT, -0.3g decel	1,810	1,276
Warning Algorithm with POV Deceleration Information		
Imminent: 1.5sec RT, -0.5g decel	943	100
Cautionary: 2.5sec RT, -0.3g decel	63,100	57,917

C.9 Summary

The computer simulation tool REAMACS (Rear-end Accident Model and Countermeasure Simulation) has been extended and used to compute metrics of performance that would result from ideal deployment and usage of FCW systems]. The work reported here uses two primary metrics associated with rear-end countermeasure performance. First, the REAMACS simulation tool is used to estimate the *potential reduction in relative harm* that FCWs may provide. Relative harm is computed over a set of simulated rear-end crash scenarios, and is defined as the ratio of the sum of the squared impact speeds for a vehicle equipped with a FCW to the same metric computed for a vehicle without the FCW. Second the In-Path Nuisance Alert Code (IPNAC) tool computes a metric called the *relative frequency of in-path nuisance alerts* that addresses the nuisance alerts likely to accompany the deployment of FCWs. In-path nuisance alerts are alerts issued by a FCW in response to a POV located in the host vehicle's path in situations considered to be non-alarming by the driver.

Simulation studies are done using a warning algorithm based on closing speed and a simple model of driver reaction to an alert, and another algorithm which also uses information about the POV deceleration. Vehicle pair speed and headways collected from Interstate 40 near Albuquerque by the Federal Highway Administration (FHWA) are used as initial conditions for the simulation work. Although this is the best database available to CAMP, the degree to which the particular database characteristics influence the simulation results is unknown. Because the database does not include vehicle accelerations, there are no stopped vehicles, and the simulation crash set significantly under-represents the frequency of rear-end crashes with stopped POVs. The database also is only highway data and therefore cannot be assumed to represent vehicle pair characteristics of other roadway types. These caveats highlight the need for more data on actual vehicle-following and braking behavior to provide more accurate estimates of potential benefits of FCW deployment. The modeling work also assumes perfect sensing by the FCW system and 100% compliance of drivers to warnings. Nuisances and false alarms due to out of path objects or sensing errors are not treated either.

The results for potential reduction in relative harm reported in this document do not take into account the possible effect of nuisance alerts on the willingness of drivers to heed the warnings or even to use the system. Therefore the results reported here are only a first-order estimate of benefits, and probably an upper bound on the actual benefits that may occur with deployment. The key premise of CAMP, is the *realizable reduction in relative harm* which would result from the deployment of FCWs would depend not only on the apparent benefits, but also on the possible effect of nuisance alerts on the willingness of drivers to use a FCW and heed the warnings. The benefits accrued when considering this effect might be called "second-order" benefits. This estimation of second-order benefits is not done in this report, however the first-order results reported provide information that may be used with the results of the human factors studies currently underway to estimate a realizable reduction in harm.

It is found that a target sensor that can support warnings at a 75-meter range provides at least 94% of the potential reduction in relative harm estimated for a sensor with unlimited range. There is a potential for FCWs to reduce relative harm by up to 67 percent using only the cautionary crash alert proposed, along with a sensor that supports a 75 meter warning range. If

used alone, an imminent crash alert, has a potential for only 20% reduction in relative harm – a warning of this type, used alone, occurs too late for much benefit with decelerating POVs. When lead vehicle information is considered, there is a potential to reduce relative harm up to 81% using a set of algorithm parameters corresponding to both the cautionary and imminent parameters, and a sensor that supports a 75 m warning range.

It is possible, however, that if simulation studies included a more accurate representation of the frequency of collisions involving stopped lead vehicles, a longer sensing range might be found to be beneficial.

An approach to categorizing all FCW alerts is suggested. In an observation there are more types of alerts than simply “nuisance” alerts and “helpful” alerts, and in fact, cases are shown where over 80% of all alerts are neither of these, but are perhaps “reinforcing” alerts issued in threatening situations in which the driver is already acting appropriately.

Estimates of the expected exposure of a driver to in-path nuisance alerts are sensitive to model assumptions regarding braking levels that drivers are comfortable using in situations they consider non-alarming. For the cautionary crash alert design suggested, a rough scaling analysis estimates that 28 in-path nuisance alerts for every rear-end crash with an impact speed of ten miles per hour or greater. This scales to one in-path nuisance alert per 4.2 years. For the imminent crash alert, simulation predicts 1.3 in-path nuisances per rear-end crash with impact speeds of at least ten miles per hour. Future experimental studies are needed to provide a more accurate “scaling” for use with the simulation results.

Simulation suggests that use of information about POV deceleration by a warning algorithm may improve performance of the FCW. Such information has the potential to increase the potential reduction in harm and to also reduce the need to tradeoff between reducing relative harm and increasing the in-path nuisance alert rate. By adding POV information to the imminent crash alert, the potential for reduction in relative harm increases from 20% to 81%, however, the corresponding in-path nuisance alert rate increases from 1.3 to 13.5 per rear-end crash with impact speed of ten miles per hour or more. By adding both POV deceleration information and varying the warning algorithm design; a potential reduction in relative harm nearly equal to that of the cautionary crash alert can be achieved. (79%) While the in-path nuisance rate drops from 28 to 2.3 alerts per rear-end collision, with impact speed of ten miles per hour or greater.

In practice, in-path nuisance alert rates may be different than reported here for warning algorithms that use lead vehicle deceleration information. There are two reasons. First, this work studies a particular class of such warning algorithms, which is those algorithms that assume the lead vehicle will continue braking at its current deceleration until it stops. The simulated situations, however, match this same scenario – the lead vehicle brakes completely to a stop. In practice, many nuisance alerts will occur for these algorithms when the lead vehicle brakes only momentarily, and so the in-path nuisance rate is likely to be higher in practice for this set of algorithms. Second, warning algorithms can use different assumptions about the future braking levels of the lead vehicle. These other algorithms are not studied here.

The simulation results suggest it is possible to define a FCW warning algorithm capable of triggering alerts which are timely enough to significantly reduce rear-end crash harm while not

producing so many in-path nuisance alerts that drivers reject the system, nullifying any overall benefit. This conclusion is based on a proposed model that defines alarming situations by the braking levels necessary to avoid a collision.

Effects of the sensitivity of the computed results to model parameters representing both lead and SV deceleration magnitudes are presented. Differences in results created by using a different day's data set from the same highway are also presented. In both cases, in-path nuisance rates may change several-fold, and the reduction in harm values may shift as well. Sensitivity studies suggest cautious use of quantitative results from this report; results are best interpreted as indicative of the general magnitude and the qualitative dependence of results on parameters.

C.10 References

- [1] *Development and validation of functional definitions and evaluation procedures for collision warning / avoidance systems.* (November 1996). CAMP revised technical proposal submitted to NHTSA in response to cooperative agreement program number DTNH22-95-R-07301.
- [2] E. Farber & M. Huang, Rear-end collision-warning algorithms with headway warning and lead vehicle deceleration information. (November 1995). *Proc. 2nd World Congress on Intelligent Transport Systems.* Yokohama.
- [3] E. Farber. Using the REAMACS model to compare the effectiveness of alternative rear-end collision warning algorithms. (April 1994). *Proc. IVHS America Fourth Annual Meeting.* Atlanta.
- [4] E. Farber and M. Paley, "Using freeway traffic data to estimate the effectiveness of rear-end collision countermeasures," *Proc. IVHS America Third Annual Meeting*, Washington, D.C., Apr. 1993.
- [5] E. Farber, *REAMACS (Rear-end accident model and countermeasure simulation) fundamental assumptions.* (June 1997). Presentation to the ITS America Safety and Human Factors Committee.
- [6] E. Farber, M. Janoff, S. Cristinzio, J. Blubaugh, W. Reisner, & W. Dunning. (1974) *NCHRP Report 154: Determining pavement skid resistance requirements at intersections and braking sites.* TRB, National Research Council, Washington D.C..
- [7] E. Farber. (1996). Adaptive cruise control as collision avoidance – a modeling exercise," *Proc. 3rd Annual World Congress on Intelligent Transport Systems*, Orlando.
- [8] Najm, W. G., Mironer, M. S., & Yap, P. K. W. (October 1996). Preliminary safety benefits of a rear-end crash warning system, in *Preliminary Assessment of Crash Avoidance Systems Benefits*, NHTSA Benefits Working Group.

- [9] Sanneman, D., Prevallet, V., & Burns, M. (February 1997). *Mathematical modeling and simulation for forward-looking collision avoidance*. Frontier Engineering, Inc. Report to NHTSA in accordance with contract DTNH22-93-C-07326.
- [10] Wang, J.-S., Knipling, R. R., & Blincoe, L. J. (April 1996). Motor vehicle crash involvements: a multi-dimensional problem size assessment. *Proc. ITS America 6th Annual Meeting*. Houston.
- [11] Olson, P., Cleveland, D., Fancher, P., Kostyniuk, L., & Schneider, W. (1984). *Parameters affecting stopping sight distance*. NCHRP Report 270. TRB, National Research Council, Washington, D.C.
- [12] Liebermann, D. G., Ben-David, G., Schweitzer, N., Apter, Y., & Parush, A. (1995). A field study on braking responses during driving. Part I: Triggering and modulation. *Ergonomics*, Vol. 38, No. 9, pp. 1894-1902.
- [13] Schweitzer, N., Apter, Y., Ben-David, G., Liebermann, D. G., & Parush, A. (1995) A field study on braking responses during driving. Part II: Minimum driver braking times. *Ergonomics*, Vol. 38, No. 9, pp. 1903-1910, 1995.
- [14] Knipling, R. R., Wang, J.-S., & Yin, H. M. (May 1993). *Rear-end crashes: problem size assessment and statistical description*. National Highway Traffic Safety Administration (NHTSA) technical report, DOT HS 807 994.
- [15] Prynne, K. & Martin, P. (1995). *Braking behavior in emergencies*. Society of Automotive Engineers 950969.
- [16] van der Horst, A. R. A. (1990). A time-based analysis of road user behavior in normal and critical encounters. T.N.O. Institute for Perception. Soesterberg, the Netherlands.
- [17] Fancher, P., Ervin, R., Sayer, J., Hagan, M., Bogard, S., Bareket, Z., Mefford, M., & Haugen, J. (March 1997). *Intelligent cruise control field operational test*. Interim report for NHTSA contract DTNH22-95-H-07428, University of Michigan Transportation Research Institute report UMTRI-97-11.
- [18] Wilson, E. E. (1940). Deceleration distances for high-speed vehicles. *HRB Proceedings*, Vol. 20.