

Fleetwide Safety Benefits of Production Forward Collision and Lane Departure Warning Systems

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ABSTRACT

Forward Collision Warning (FCW) and Lane Departure Warning (LDW) systems are two active safety systems that have recently been added to the U.S. New Car Assessment Program (NCAP) evaluation. Vehicles that pass confirmation tests may advertise the presence of FCW and LDW alongside the vehicle's star safety rating derived from crash tests. This paper predicts the number of crashes and injured drivers that could be prevented if all vehicles in the U.S. fleet were equipped with production FCW and/or LDW systems. Models of each system were developed using the test track data collected for 16 FCW and 10 LDW systems by the NCAP confirmation tests. These models were used in existing fleetwide benefits models developed for FCW and LDW.

The 16 FCW systems evaluated could have potentially prevented between 9% and 53% of all rear-end collisions and prevented between 19% and 60% of injured (MAIS2+) drivers. Earlier warning times prevented more warnings and injuries. The lower operating speed thresholds of some systems also greatly affected benefits estimates. The results of this study suggest that future FCW testing protocols should also include low-speed warnings under 25 mph because of the potential safety benefits of these systems.

For LDW systems, the 10 systems tested had similar benefits if distance to the lane marking was used as the metric for delivering the warning. For all vehicles, the number of crashes prevented varied from 29% to 32% and the number of injured (MAIS3+) drivers prevented varied from 25% to 27%. LDW benefits are more sensitive to Time to Lane Cross (TTLC) as a metric for warning delivery. The number of crashes varied from 13% to 47% and the number of injured drivers varied from 10% to 42% when TTLC was the metric used to deliver the LDW. This result suggests that future LDW tests should consider TTLC as a metric in addition to distance to lane cross.

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INTRODUCTION

Forward Collision Warning (FCW) and Lane Departure Warning (LDW) are the two active safety systems that were recently added to the U.S. New Car Assessment Program (NCAP). Vehicles that pass confirmation tests on a test track can advertise the presence of FCW and/or LDW along with the vehicle's star safety rating. In order to pass the confirmation tests, the systems must warn the driver in a prescribed set of test conditions specified by the National Highway Traffic Safety Administration (NHTSA). The design and limitations of the systems can vary widely by automaker. The time to collision (TTC) or time to lane cross (TTLC) at which the warnings are delivered are different between systems. Even a small amount of additional time for evasive maneuvers can mean the difference between a driver being able to avoid a collision and having a crash. System limitations also play an important role

in the expected fleetwide benefits of a proposed system. An example of a system limitation is if a system only operates within a fixed range of vehicle travel speeds.

Previous benefits estimates models have often used a single, often hypothetical system specification for FCW or LDW. The unique contribution of the current study is to use the actual characteristics of the systems to compare the effectiveness of different production systems. The models take into account both the system design (i.e. warning timings) as well as system limitations (e.g. operating speed constraints) to predict benefits.

The objective of this study is to compare the expected safety benefits of 16 FCW and 10 LDW systems equipped as optional equipment on 17 production vehicles. The expected benefits will be computed as the number of collisions and seriously injured drivers that could be prevented if all vehicles in the U.S.

vehicle fleet were equipped with the systems. To make benefit estimates, we will use previously developed methodologies to reconstruct large nationally representative samples of crashes from the National Automotive Sampling System Crashworthiness Data System (NASS/CDS) [1-2]. Models of the production FCW and LDW systems will be derived from test data obtained during NCAP confirmation tests. As part of the NCAP, model year 2012 and 2013 vehicles manufactured by Acura, BMW, Cadillac, Chevrolet, Dodge, Ford, Infiniti, Mercedes, and Volvo were evaluated.

METHODOLOGY

Benefits Estimates for Active Safety Systems

Overview of Approach

The objective of a fleetwide benefits estimate is to predict the number of crashes and/or injuries and fatalities that a proposed system could prevent if deployed in the vehicle fleet. These benefit estimates are predictive and are generally made before a proposed system is widely deployed in the vehicle fleet. After a system is widely developed, retrospective analyses of crash databases can be performed to assess the safety benefits of the deployed system. FCW and LDW are still in early stages of adoption and are generally only available as optional equipment. Another active system, Electronic Stability Control (ESC), has been available as optional equipment since the early 2000's and is now required on all new vehicles sold in the U.S. ESC is sufficiently deployed and retrospective studies have been performed to assess its effectiveness [4-5].

A commonly proposed methodology for fleetwide benefits estimates for proposed systems is to use mathematical models to simulate crash risk before and after a system is applied. These mathematical models are then applied in a number of crash scenarios or initial conditions that are proportional to the vehicle fleet. Combined, these simulations can predict the proportion of crashes or injuries that could be prevented by the introduction of a proposed system. The Advanced Crash Avoidance Technologies (ACAT) program sponsored by the National Highway Traffic Safety Administration (NHTSA) conducted several studies using a framework summarized in Figure 1 [6-7]. ACAT projects developed Safety Impact Methodologies (SIMs) for predicting benefits of FCW and LDW [8-9].

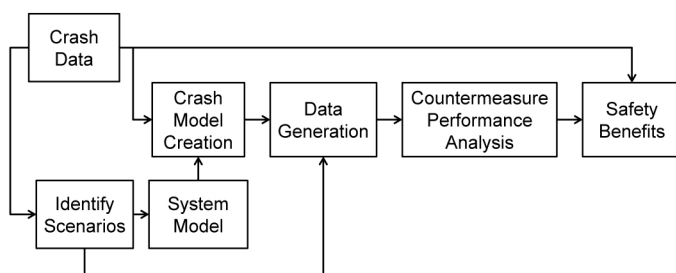


Figure 1. Safety Impact Methodology Proposed by the Advanced Crash Avoidance Technologies program.

In previous research studies, the authors of the current paper developed safety benefits estimates models for FCW and LDW for the U.S. vehicle fleet [1-2]. Compared to past benefits estimate techniques, the models developed by the authors use mathematical models to quickly simulate a large sample of approximately 1000-2000 real-world collisions as if the driver had either FCW or LDW.

The methodology uses modeling techniques that use data from the nationally representative National Automotive Sampling Systems, Crashworthiness Data Systems, or NASS/CDS. In order to be included in NASS/CDS at least one passenger vehicle must have been towed from the crash scene. Field investigation teams throughout the U.S. perform in depth investigations on approximately 5000 collisions per year. The investigations include preparing photographs/diagrams of the crash scene, measuring vehicle damage, and collecting medical records of injured occupants. To generate a nationally representative sample, the NASS/CDS sample designers assign each case a weight. The weight represents the number of similar collisions that occurred during the sample period because cases are not randomly selected. All of the analysis in this paper used the NASS/CDS sample weights.

The target populations for FCW and LDW were selected from several years of NASS/CDS. Cases with applicable pre-crash scenarios were first selected, and then cases with missing data required in the models were discarded. The target population for FCW was rear-end collisions. The target population for LDW was single vehicle run off road crashes. Applicable crashes were identified using previously developed pre-crash scenarios that use accident type, critical pre-crash event, and pre-crash movement variables [3].

NASS/CDS years 2007-2011 were used to select cases for the LDW simulations and NASS/CDS years 1997-2008 were used to select cases for the FCW target population. Years 2007-2011 are the last five years of data available at the time of writing and provided a large sample of road departure crashes to simulate. The FCW target population was developed with a larger range of NASS/CDS years for two reasons: 1) more reconstruction information that is often missing (e.g. ΔV) was required for modeling FCW crashes and 2) vehicle inertial properties not included in the published data had to be manually compiled from the NASS/CDS online case viewer. As this manual extraction process was time consuming, we did not include the most recent years of NASS/CDS in this study.

Benefits Estimates Framework

The benefits of the system can be stated simply as

$$\text{Benefits} = \frac{\# \text{ without system} - \# \text{ with system}}{\# \text{ without system}}$$

where the number (# symbol) can represent the number of crashes, injuries, or fatalities. The number without the system is determined from the real-world data and the number with the system is the result of computational simulation.

The number of crashes with the system is found by summing over all crashes and unknowns:

$$\# \text{ Crashes with system} = \sum_{i=1}^N \sum_{j=1}^M w_i w_j f(\theta_i, \phi_j)$$

where N is the total number of collisions, M is the number of simulations representing different drivers per collision, w_i is the weight for the collision, w_j is the weight of the simulation, and $f(\theta_i, \phi_j)$ is the simulation result and has a value of 0 for a collision that is avoided and 1 for a collision that is not avoided. The driver reaction to a system in a retrospective crash database is unknown. As a result, in this framework each collision in a given dataset is simulated multiple times to account for unknowns. Using weights that describe how likely a driver reaction is, w_j , the expected number of collisions is aggregated by summing over all simulations. The simulation weight, w_j , is between 0 and 1. These weights can be derived from probability distributions of reaction times, for example. The total number of crashes in a population is then aggregated using a collision weight, w_i , that describes how likely a crash was to occur in the population. The case weight, w_i , is the number of similar collisions that exist in the population. Many nationally representative crash databases include case weights to account for nonuniform sampling of crashes.

The simulations have two types of input represented by the vectors θ_i and ϕ_j . θ_i is a vector representing the relevant road, vehicle, and occupant characteristics that are unique to each crash. This can include the roadway type, surface conditions, vehicle type, occupant age, and seat belt status. The data for θ_i is extracted from the real-world crash data and does not vary between simulations of a case. The vector ϕ_j represents the driver vehicle control characteristics that will affect the driver's response to a proposed system in the simulation. These factors can include what action the driver will take, e.g. brake or steer, driver reaction time, and driver input magnitudes.

Because the proposed method is based on simulation, a discrete number of simulations, M , and crashes, N , are summed. In a purely probabilistic method, both the summations would be replaced by integrals over some probability density functions that describe the distributions of crashes and driver reactions, respectively. However, such distributions are often intractable because of complex interactions between crash variables and outcome. The current method is both probabilistic and computational in that it simulates all cases in a target population and weights these simulation results to represent the true distribution of crashes. The crash and injury outcomes are computed using computational models.

The number of injuries expected with a system is not only a function of whether a crash occurs or not but also the severity of the crash if it does occur:

$$\# \text{ Injuries with system} = \sum_{i=1}^N \sum_{j=1}^M w_i w_j g(\theta_i, \gamma_j)$$

where $g(\theta_i, \gamma_j)$ is an injury risk function that describes the probability of an injury occurring given some or all the crash conditions in θ_i and a crash severity measure, γ_j . Common crash severity measures are travel speed of the vehicle or change in velocity during the impact, ΔV . In this framework severity is also determined from simulation and is a function of the initial conditions of the crash (θ_i) and the driver input (ϕ_j).

The following two sections summarize the approaches for the FCW and LDW benefits estimate models.

FCW Benefits Estimate Model

FCW systems warn the driver when a rear-end collision with a vehicle in front of the equipped vehicle is likely. A simple metric that is used by many FCW to determine when to deliver the warning is Time to Collision (TTC). In its simplest form, TTC is ratio of the instantaneous range to the range rate of the vehicle or object that is a collision risk. Range is the distance from the equip vehicle to another vehicle, and range rate is the relative velocity between the vehicles.

In order to model the effect of FCW, we created a model of how drivers would likely react if they were given a warning before a crash. Retrospective crash data shows that in tow-away rear impact collisions braking is the primary avoidance maneuver and steering alone is rare. The model we developed assumes the driver will only brake to avoid a rear-end collision. Past studies have found that steering avoidance maneuvers were present in less than 5% of rear-end collisions [10]. After the FCW is delivered, the driver has a reaction time before applying the brakes. To model the reaction time, we used a representative distribution developed by Sivak *et al.* that has been used in collision avoidance models previously [11, 12, 13, 14]. The distribution is lognormal having a mean reaction time of 1.21 s and a standard deviation of 0.63 s.

In real-world crash data, the driver characteristics and reaction time are unknown. In order to model variability in driver reaction time, we simulated four (4) driver reaction times for every NASS/CDS crash. To select these four characteristic reaction times, the lognormal distributions was separated into four quartiles representing 25% of the area under the probability density function and the centers of these four regions were used, as shown in Table 1. To simulate benefits, each simulation with the four driver reaction times was assigned 25% of the NASS/CDS case weight. In this study, all drivers that were presented a warning were assumed to react by braking after the specified reaction time. Depending on the

system activation and vehicle speeds in the simulations, however, not all reaction times would cause braking before a crash occurred.

Table 1. Four Reaction Times used for FCW Model

Case	Reaction Time (s)
1	0.55
2	0.87
3	1.25
4	1.98

In the model, the warning would allow the driver to apply the brakes earlier than they would have without FCW. This additional braking time and/or magnitude will either prevent the collision or reduce the severity of collisions that do occur. The change in velocity during the impact, often denoted as ΔV or delta-V, has been found to be well correlated with injury outcome [12-13]. Using the same reconstruction framework used by the NASS/CDS investigators, we derived what the ΔV would have been after additional braking, ΔV_1^* , as a result of FCW

$$\Delta V_1^* = \Delta V_1 - \frac{\gamma_1 \gamma_2 m_2}{\gamma_1 m_1 + \gamma_2 m_2} P_{brake}$$

where ΔV_1 is the original change in velocity estimated by the NASS/CDS investigators, γ is the effective mass coefficient, m is the mass of the vehicles, and P_{brake} is the braking impulse after FCW. The effective mass coefficient, γ , is

$$\gamma = \frac{k^2}{k^2 + h^2}$$

where k is the radius of gyration of the vehicle, and h is the offset from the damage center to the vehicle center of mass. The effective mass coefficient estimates the amount of crash energy that is transformed to linear change in velocity as opposed to rotational velocity change. This methodology assumes that the lead vehicle is standing still so that the relative velocity at impact equals the velocity of the striking vehicle. As such, we only predicted benefits for rear-end collisions in which the lead vehicle was stopped prior to impact as indicated by the NASS/CDS investigators.

Injury risk reduction was predicted by a logistic regression model with ΔV as the predictor. The model predicted the probability of an injured driver. Injury was defined as a driver Maximum Abbreviated Injury Score (MAIS) of two or greater (MAIS2+). The intercept for the model was -6.068 and the coefficient for ΔV was 0.1, where the units of ΔV were kilometers per hour.

LDW Benefits Estimate Model

LDW systems warn the driver when the vehicle is drifting out of his or her lane. Similar to the use of TTC with FCW, LDW systems can use Time to Lane Cross (TTLC) to deliver a

warning. TTLC is the ratio of the lateral velocity to the lateral distance to the road's edge marking. Another metric used to deliver a warning is the lateral distance to crossing the lane line. As specified in the following section, the NCAP confirmation test requires that warnings be delivered within a specified distance before and after the vehicle crosses the lane line. Because the NCAP tests are only run at a single test condition, it is not clear if the tested systems use TTLC or distance to lane cross as a metric for delivering a LDW. Therefore, we will investigate benefits for systems using both TTLC and distance to lane cross as a metric for LDW delivery.

Without LDW, the model assumed the driver became attentive once the vehicles leading tire reached the edge of the paved shoulder. Steering started after a reaction time. With LDW, the warning in the model was delivered when the vehicle's leading wheel was a specified distance from the lane marking.

A LDW alerts the driver to steer back toward the road after a departure occurs. In order to model this behavior, we specified a steering reaction time and steering response derived from driving simulator experiments in the literature. Suzuki and Jansson [15] found that reaction time of distracted drivers varied from 0.38 s to 1.36 s depending on warning modality and if the driver was informed of the LDW system function or not. Kozak *et al.* [16] performed a simulator experiment using sleep deprived subjects. They found the average reaction time of a LDW was 0.62 s. In the current study, we used two reaction times of 0.38 s and 1.36 s to represent a fast response and a slow response time drivers.

The steering was characterized by the minimum radius of curvature permitted by friction:

$$R_{\min} = \frac{v_D^2}{\mu g} \quad (1)$$

The off-road coefficient of friction, μ , was assumed to equal 0.5 for all cases. This method of characterizing steering yielded maximum steering angles similar to those reported in a test track experiment by Mazzae *et al.* (approximately 53 degrees) [17].

Our hypothesis was that the probability of a crash was influenced by two factors: a) the lateral distance traveled from the road edge and b) the total distance traveled off road. In order to create a model that had both of these characteristics, we separated the roadside into discrete bands, as shown in Figure 2. Vehicles that were involved in crashes, i.e. those from a crash database, have trajectories on their way to impacting objects that pass through each roadside band ($k = 1, 2, 3, \dots$). Retrospective crash data was used to determine the probability of having a crash based upon the length of the trajectory in each band. This model can then be used to predict the probability of a crash during a simulated trajectory.

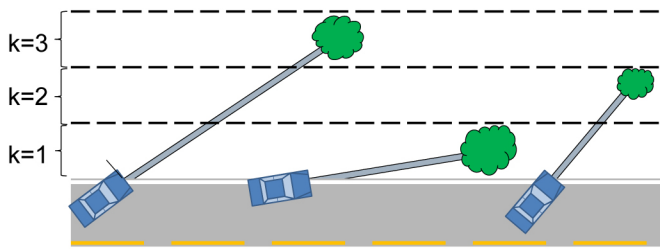


Figure 2. Examples of Vehicle Paths and Roadside Bands.

Using a sample of crashes and trajectories, the probability of a crash on the simulated trajectory j can be found as

$$P[Crash_j] = 1 - \prod_{k=1}^K \exp\left(-\frac{C_k L_{j,k}}{\gamma_k}\right).$$

where C_k is the number of crashes in band k , $L_{j,k}$ is the length of the simulated trajectory in band k , and γ_k is the total trajectory length in band k from the crash data. The crash data used to develop this model was a special subset of NASS/CDS cases investigated as part of the National Cooperative Highway Safety Research Program (NCHRP) Project 17-22 or NCHRP 17-22 [18]. Additional crash reconstructions not included in the original NASS/CDS data were performed for 890 collisions occurring between 1997 and 2001.

Most crash databases, such as NASS/CDS are missing important parameters for modeling lane departure crashes. In order to model these missing variables from NASS/CDS, we created statistical models using the NCHRP 17-22 database to predict the missing variables as a function of other crash database variables. The variables modeled were:

- Velocity at departure
- Angle at departure with respect to the road
- Radius of curvature of the road
- Shoulder width

Details about the models developed for these missing variables are included in the [appendix](#).

Injury risk was predicted as a logistic regression function with predictors of departure speed and seatbelt status. The function predicted the probability of a seriously injured driver at a MAIS3+ level. MAIS3+ was used for the road departure model because serious injuries are more often observed in road departure crashes compared to rear-end collisions. The injury models were developed using the same NCHRP 17-22 dataset that was used to develop models for missing data because of the reconstructed departure velocities available in this dataset and not available in NASS/CDS. Departure speed was used instead of ΔV as a measure of crash severity because ΔV is not reconstructed in most crashes with fixed roadside objects. The injury model also included rollover events, which also do not have reconstructed ΔV . The intercept of the model was -3.03 , the departure speed (kph) term was 0.0277 , and the seat belt term (1 for belted, 0 for unbelted) was -1.91 .

NCAP Confirmation Test Data

The NCAP confirmation tests are performed on a test track with the goal to verify the function of FCW and LDW. Vehicles tests can either pass or fail the confirmation test. No rating system is generated from the tests that describe the systems' performance. [Table 2](#) lists the vehicles that were tested for FCW or LDW systems. Three vehicles were tested for both FCW and LDW but did not have an accompanying test report for one of the tests.

Table 2. Vehicles Tested in FCW and LDW Confirmation Tests

Model Year	Make	Model	FCW	LDW
2012	A	Veh. 1	x	x
2013	A	Veh. 2	x	x
2012	B	Veh. 1	x	x
2013	C	Veh. 1	x	x
2013	D	Veh. 1	x	x
2012	D	Veh. 2	x	x
2012	E	Veh. 1	x	
2012	E	Veh. 2	x	
2013	E	Veh. 3	x	
2013	E	Veh. 4	x	1
2012	F	Veh. 1	x	
2012	G	Veh. 1	x	x
2012	G	Veh. 2	x	1
2012	H	Veh. 1	x	x
2012	H	Veh. 2	x	x
2012	H	Veh. 3	1	x
2012	I	Veh. 1	x	

¹Passed confirmation test, but no test report available

The following two sections briefly describe the test conditions.

FCW Confirmation Test

The FCW confirmation tests are performed on a test track where the subject vehicle, or vehicle under test, approaches a lead, or principal other, vehicle that is a midsize sedan. [Table 3](#) summarizes the three test conditions [19]. The first is a lead vehicle stopped, the second is a lead vehicle decelerating, and the third is a lead vehicle traveling at a constant speed slower than the subject vehicle. A total of 7 trials are performed for each of the three test conditions. In order to pass each test condition, a FCW must be delivered at a TTC that is greater than specified thresholds in 5 out of the 7 of the trials.

Additionally, to pass the test no two consecutive trials must fail to deliver a FCW by the specified TTC. If the first 5 trials are passed, the last two in the test condition may be skipped. In