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Event Data Recorder Trigger Probability in the Crash Investigation Sampling System Database

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Abstract

The objective of this study was to quantify the field performance of passenger vehicle event data recorders (EDRs) in recording data into non-volatile memory at the 8 km/h delta-v (Δv) trigger threshold specified by Title 49, Part 563 of the Code of Federal Regulations (Part 563). Part 563 applies to passenger vehicles manufactured on or after September 1, 2012. The trigger threshold is distinct from the threshold required to deploy an airbag. Events meeting the trigger threshold will cause data to be preserved on the EDR even if airbags are not deployed. This is the first study to quantify EDR trigger threshold performance. This data is valuable in the evaluation of sub-airbag deployment crashes. The study was accomplished via analysis of EDR and reconstructed Δv data from 3,960 cases in the Crash Investigation Sampling System (CISS) database maintained by the National Highway Traffic Safety Administration (NHTSA). The binary presence or non-presence of an event on the EDRs of vehicles exposed to a collision was compared to the CISS reconstructed Δv for each vehicle. Logistic regression models were developed to predict the probability of an event present on the EDR at the trigger threshold. We found that vehicles manufactured by Toyota had lower Δv thresholds compared to other manufacturers. For Toyota manufactured vehicles, the probability of an EDR event at 8 km/h ranged from 87% to 99%. EDR event probabilities for non-Toyota vehicles in vehicle-to-vehicle collisions ranged from 58% to 93% for Part 563 compliant vehicles and 33% to 83% for pre-Part 563 vehicles. The persistence of EDR events in memory was analyzed using the number of ignition cycles present between events and imaging of the EDR, finding average duration of 3,595 ignition cycles for pre-existing EDR events unrelated to the CISS case.

Keywords

EDR, CISS, Trigger threshold, Part 563, Probability

Introduction

The stated purpose of Part 563 is to help ensure that EDRs record, in a readily usable manner, data valuable for effective crash investigations and for analysis of safety equipment performance [1]. EDR data is obtained from a vehicle through a process where the EDR memory is imaged, and a report generated. The CISS database is one of the databases maintained by the NHTSA for the purpose of collection of crash data in support of the NHTSA's mission to reduce crashes, injuries, and deaths on the highways of the United States. CISS collects crash and injury data on crashes across the spectrum of crash severity to create a nationally representative sample [2]. A requirement for CISS cases is that at least one vehicle was towed for any reason. This is a loosening of the requirement in the predecessor National Automotive Sampling System (NASS) database where at least one vehicle had to be towed due to damage. CISS investigators use accident reconstruction techniques to quantify the severity of crashes with the metric of Δv, the change in velocity due to impact. When possible, CISS also obtains EDR data from the crash-involved vehicles.

The NHTSA uses the Bosch Crash Data Retrieval (CDR) system to image EDRs and generate the EDR data report for CISS cases. Compared to the predecessor NASS database, CISS collects EDR data in a larger percentage of cases. Though EDR data including Δ*v* is collected by CISS, the Δ*v* reported in a CISS case is derived from manual reconstruction of the crash.

Reconstructions in CISS use field investigation data in conjunction with the NHTSA's WinSmash software to calculate damage energy and Δ*v* [3, 4]. Different WinSmash algorithms are used depending on the available field evidence. The most common is the damage algorithm, which uses measured vehicle crush profiles as an input along with vehicle characteristics including stiffness coefficients. The next most common is the missing vehicle algorithm, which uses a ratio of vehicle stiffness and the damage energy calculated for a measured collision partner to estimate damage energy and Δ*v* for a vehicle that was not measured for a crush profile. A small percentage of NASS and CISS cases use vehicle trajectory data in addition to damage energy in the calculation of Δ*v*. WinSmash reconstructions such as those in CISS and its predecessor NASS have the characteristic of overestimating damage energy at lower crash severities and underestimating at higher crash severities, and as a result overestimating Δ*v* at low crash severity and underestimating Δ*v* at high crash severity [5, 6].

Logic for data recording by EDRs is specified in Part 563. EDRs record data when crash severity reaches a certain threshold. This threshold is defined as the trigger threshold in Part 563. Recorded data are stored as events. An event is defined as a crash or other physical occurrence that causes the trigger threshold to be met or exceeded, or any non-reversible deployable restraint to be deployed, whichever occurs first. The trigger threshold is distinct from the crash severity required to deploy an airbag or other non-reversible, deployable restraint. In Part 563, the trigger threshold is defined as a Δ*v* in the longitudinal direction that equals or exceeds 8 km/h (5 mph) within a 150 ms interval. For vehicles that record lateral Δ*v*, the same 8 km/h over 150 ms threshold applies in the lateral direction. There are instances where the total Δ*v* can exceed 8 km/h but the longitudinal and lateral recording threshold may not be met. For example, an event that had a 7 km/h longitudinal Δ*v* and a 7 km/h lateral Δ*v* would have an overall resultant Δ*v* of 9.9 km/h but would technically not have reached either the lateral or longitudinal trigger threshold.

Per Part 563 EDRs must capture and record specified data elements for events including longitudinal Δ*v*, ignition cycle of the crash, and ignition cycle at which the EDR was imaged. Many EDRs record optional data elements including lateral Δ*v*. The accuracy, range, and resolution of several required and optional data elements are specified by Part 563. For longitudinal and lateral Δ*v*, the required accuracy is ±10% with a range of −100 km/h to +100 km/h at a resolution of 1 km/h. In the case of events that result in an airbag deployment, the data must be locked to prevent overwriting. In the case of non-deployment events, data is written to non-volatile memory. An exception occurs if the non-volatile memory already contains data from a previous non-deployment event. In that case, the manufacturer may choose to overwrite the existing non-deployment event data with the current data, or to not record the current non-deployment data. According to this logic, a vehicle subject to Part 563 that has experienced an event meeting or exceeding the trigger threshold will have event data stored in non-volatile memory. As the trigger threshold is at a low severity level, Part 563-compliant EDRs in CISS have the capability to provide researchers with a valuable source of real-world crash data covering the spectrum of crash severity. Prior to Part 563, there was not a statutory requirement for EDR trigger thresholds.

EDRs only record Δ*v* after the trigger threshold is met and, therefore, Δ*v* for cases in which no event is present must come from a source different from the EDR. Investigators in the CISS database perform reconstructions of Δ*v* independent of EDR data. These reconstructions encompass the full spectrum of Δ*v* in CISS and provide a source of Δ*v* linked to EDR images whether the images do or do not contain an event. Reconstructions of Δ*v* have error when compared to Δ*v* reported by EDRs. Previous studies have quantified EDR performance in recording Δ*v* and compared the Δ*v* in NASS and CISS reconstructions to the Δ*v* recorded by EDRs [7, 8, 9].

Niehoff et al. compared the Δ*v* recorded by EDRs in early 2000s model year vehicles to the Δ*v* recorded by laboratory instrumentation in 34 frontal and three lateral full-scale crash tests. Their study determined that EDR Δ*v* had an average error of 6% for frontal Δ*v* with an error of 1.1% for pre-crash speed. It was also found that EDR Δ*v* was generally underreported compared to laboratory instrumentation [10].

Tsoi compared pre-crash speed and Δ*v* recorded by EDRs to laboratory instrumentation in 41 full-scale frontal crash tests of 2012 model year vehicles and saw an average error of 1% for pre-crash speed and 6.6% for Δ*v*. This study also revealed that the EDR data tended to underreport compared to laboratory instrumentation [11].

A compendium of EDR studies comparing pre-crash speed and Δ*v* recorded by EDRs to laboratory measurements was published by Bortles in 2016. This article reported over 400 crash tests comparing EDR Δ*v* to laboratory instrumentation, with model years ranging from 1998 to 2014. The authors found EDR data tended to be accurate and tended to underreport pre-crash speed and Δ*v* values [12].

A 2014 study by Wood et al. investigated the probability of airbag deployment as a function of Δ*v* in frontal impacts [13]. The probability of airbag deployment is distinct from the probability of reaching the trigger threshold defined by Part 563. This study examined 6,826 EDR reports from the NASS database. The Wood study contained EDR data from vehicle model years 1994–2011. The majority of vehicles in this study were manufactured by GM (88.8%). In this study, 44% of EDR downloads contained a deployment event, 51% contained a non-deployment event, and 5% contained no event or no data. The study showed that airbag deployment thresholds changed over time with model year 1994–2001 GM vehicles having a 50% probability of deployment at an 8 to 9.7 km/h Δ*v*. The study concluded that 2002–2011 model year GM vehicles had a 50% deployment probability at Δv between 14.5 and 16.1 km/h.

Lee et al. published a similar study on airbag deployment thresholds [14]. This study analyzed 9,499 EDR reports taken from NASS with vehicle model years 1994–2016. The study determined that airbag deployment thresholds changed over time with model year 1994–2001 vehicles having a 50% probability of deployment at a 9.7 to 11.3 km/h Δv and 2002–2016 model year vehicles having a 50% deployment probability at a 12.9 to 14.5 km/h Δv.

The Lee and Wood studies documented ranges of Δv at which airbags typically deploy. The Δv at which airbags deploy is not mandated and the algorithms that determine airbag deployment are proprietary, based on factors that each manufacturer chooses to maximize the effectiveness of the airbag system given the variables of the vehicle, occupant, and crash characteristics. In comparison, the EDR trigger threshold examined in the present study is a set value mandated by Part 563.

Little performed a study on the average number of daily ignition cycles on EDRs [15]. The goal of this study was to estimate the amount of time that had passed between the day of an event and the day the EDR was downloaded. This research showed that non-commercial vehicles had an average of six to seven ignition cycles per day recorded on their EDRs.

Previous studies have shown the differences between NASS and CISS-reconstructed Δv and EDR-reported Δv in frontal and rear impacts. Hampton and Gabler showed that frontal impact WinSmash reconstructions in NASS overestimated EDR Δv below 16 km/h and underestimated Δv above 16 km/h. The study concluded that across the complete range of Δv, the NASS reconstructions underestimated the EDR by −13.2% [5].

A study by Gabler comparing rear impact NASS reconstructions to EDR data found that the reconstructions underestimated the EDR by 4.5% on average [8].

Watson et al. compared CISS rear impact reconstructions to EDR data and showed that the reconstructions overestimated the EDR Δv when the EDR Δv was 16 km/h or less and underestimated the EDR Δv above 16 km/h, with an overall average underestimate of −4.0% [6].

The present study focused on quantifying the probability of EDRs recording an event when reaching the 8 km/h Δv specified by the Part 563 trigger threshold using the Δv reconstructed by the CISS investigation.

Methods

Event Probability

The CISS database was searched for all cases that contained an EDR image. The CISS variable EDROBTAINED defines whether the CISS investigation was able to image EDR data from a vehicle and whether that data contained an event. The EDROBTAINED variable was used to exclude cases that did not contain an EDR image. Cases with multiple impacts or rollovers were excluded using the CISS variables DVRANK and ROLLTYPE, respectively. Cases missing a CISS-reconstructed Δv were excluded. The CISS variable DVBASIS describes the WinSmash algorithm used by CISS. The cases making up the dataset were single-event cases with EDR downloads and a CISS-reconstructed planar Δv using the WinSmash damage or missing vehicle algorithm. A total of 3,960 cases were found. There were 2,540 vehicles with model year 2013 or higher. There were 1,420 vehicles with model year 2012 or lower. Impact orientation was determined using the CISS variable PDOF (principle direction of force). Frontal, rear, and side impacts were divided into four 90-degree-wide PDOF windows centered on 0, 90, 180, and 270 degrees for front, right, rear, and left, respectively. There were 2,675 frontals, 825 side, and 460 rear. As the Part 563 trigger threshold is specific to longitudinal and lateral Δv, the longitudinal and lateral Δv reconstructed by CISS were used in the analysis. Longitudinal Δv was used for front and rear impacts, lateral Δv was used for side impacts. The data consisted of 2,264 cars and 1,696 light transport vehicles (LTVs). LTVs are pickups, SUVs, and vans. This dataset was called the event dataset. The composition of the event dataset is shown in Table 1.

First-order analysis of the event dataset was performed by calculating the percentage of EDRs containing an event. This data was organized in 8 km/h bins of CISS reconstructed Δv. The analysis was performed for vehicles built prior to the Part 563 compliance date as well as vehicles built after the Part 563 compliance date.

Multivariate binary logistic regression modeling was performed on the event dataset using the lrm function from the rms package in the R statistical software [16]. This modeling was performed to determine the probability of an EDR event occurring over the range of CISS-reported Δv. Multivariate binary logistic regression, hereafter referred to as logistic regression, can be used to assess the probability of a binary yes/no event occurring given multiple predictor variables. In addition to Δv, the predictor variables investigated included vehicle type,

TABLE 1 Event dataset.

Group	Count	Avg. Δv (km/h)
Model year 2013 and newer	2,540	19.4
Model year 2012 and older	1,420	19.2
Manufactured by Toyota	698	20.1
All other manufacturers	3,262	19.1
EDR event	3,694	19.9
No EDR event	266	10.4
Cars	2,264	17.9
LTVs	1,696	20.3
Frontal	2,675	21.2
Side	825	13.5
Rear	460	19.0
Damage data	2,317	20.3
Missing vehicle	1,643	17.9
Vehicle to vehicle	3,745	18.9
Non-vehicle	215	26.4
All	3,960	19.3

vehicle manufacturer, vehicle model year, PDOF, collision partner, and WinSmash algorithm used. The logistic regression models have the form:

$$P(Event) = \left[1 + \exp(-X\beta)\right]^{-1} \qquad \text{Eq. (1)}$$

where $X\beta$ is equal to:

$$\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i$$

Each predictor variable is represented by a coefficient β_i. The predictor coefficients were fit to the binary data of EDR event/no event using the lrm function in *R*. When fitting the models to the data, each predictor value had an associated p-value indicating significance. A p-value of 0.05 or lower was considered significant. Fitting was performed stepwise where the predictor with the highest p-value was removed at each step until all remaining predictors were significant. This process led to the development of two separate logistic regression models, one model was for the majority of manufacturers, referred to as the base model. The other was for vehicles manufactured by Toyota, referred to as the Toyota model.

Variables in the logistic regression models include:

- **DV.** The CISS-reconstructed longitudinal or lateral Δ*v* in kilometers per hour.
- **Back.** When set equal to one, this variable represents vehicles that sustained a rear impact. When set equal to zero, this variable represents vehicles that experienced frontal or side impacts.
- **Old.** When set equal to one, this variable represents vehicles with model years 2012 or older, built prior to the Part 563 standard. When set equal to zero, this variable represents vehicles with model years 2013 or newer that are subject to the Part 563 standard.
- **LTV.** When set equal to one, this variable represents LTVs. When set equal to zero, this variable represents passenger cars.
- **Missing.** When set equal to one, this variable represents cases where the CISS reconstruction used the missing vehicle algorithm in WinSmash. When set to zero, cases using the WinSmash damage algorithm are represented.
- **Non-Vehicle.** When set equal to one, this variable represents cases where the collision partner was not another vehicle. When set to zero, vehicle-to-vehicle collisions are represented.

Logistic regression models can be overfit to the data used to build them, leading to overly optimistic predictions. To determine the performance of the models on datasets other than the data used in construction, bootstrap validation was performed on the final logistic regression models. Bootstrap validation returns estimates of the area under the receiver operating characteristic curve (AUROC) that are corrected for optimism [16]. AUROC is a metric for evaluating the discrimination of logistic regression models and ranges from 0 to 1.0. AUROC values of 0.5 and lower suggest the model has no discrimination ability while an AUROC value of 1 indicates that the model has correctly categorized all of the data [17]. The bootstrap method involves resampling the input data, refitting the model to the resampled data, evaluating the performance of the new model on the refit data, evaluating the performance of the refit model on the original input data, and comparing the difference in performance of the two models. This sequence is performed many times. The average of the difference in performance for all runs is subtracted from the original performance to arrive at the corrected, non-optimistic performance of the model. The bootstrap validation procedure was performed using the validate function from the rms package in R using 800 runs. The bootstrap validation methodology has been previously used in the validation of logistic regression models based on the NASS database [18].

Error Analysis

A subset of the data was used to analyze the error between the CISS-reconstructed Δ*v* and the Δ*v* determined by the EDR. This analysis required cases that had both CISS-reconstructed and EDR-reported Δ*v*. Though the Part 563 trigger threshold is a Δ*v* of 8 km/h, EDRs often record data below this value, allowing quantification of CISS reconstruction error in comparison to EDR Δ*v*. The dataset used to analyze error consisted of 2,900 cases where there was a single-event CISS-reconstructed Δ*v* and a corresponding EDR-reported Δ*v*. This dataset was called the error analysis dataset and contained 2,164 frontal impacts, 399 side impacts, and 337 rear-end impacts. In 143 of the cases, the EDR recorded a Δ*v* less than 8 km/h. Table 2 shows the composition of the error

TABLE 2 Error analysis dataset.

Group	Count	Avg. CISS Δ*v* (km/h)	Avg. EDR Δ*v* (km/h)
Model year 2013 and newer	2,209	20.3	23.4
Model year 2012 and older	691	20.9	22.9
EDR Δ*v* < 8 km/h	143	11.0	5.5
Cars	1,682	21.4	24.4
LTVs	1,218	19.1	21.7
Frontal	2,164	21.8	25.2
Side	399	13.4	15.8
Rear	337	20.0	19.9
Damage data	1,690	21.2	25.3
Missing vehicle	1,210	19.4	20.4
Vehicle to vehicle	2,751	20.1	22.5
Non-vehicle	149	27.5	37.3
All	2,900	20.4	23.3

analysis dataset. Δv recorded by the EDR were collected and averaged in 8 km/h bins from 0 to 120 km/h. The associated CISS-reconstructed Δv were collected and averaged for comparison to the EDR Δv. Linear regression was performed for the entire dataset as well as for subsets including model year split at 2013, impact direction, WinSmash algorithm, vehicle-to-vehicle collisions, and non-vehicular collisions. Linear regression was performed for each subset as a whole and for EDR Δv ranges 0 to 16 km/h and 16 km/h and above.

Event Persistence

Analysis was performed on the persistence of EDR events. As EDRs record data over the lifetime of the vehicle, they may contain events that occurred prior to the subject crash investigated by CISS. The CISS variable CDCEVENT describes whether an event on an EDR download was related to the subject CISS case or not. Data for this analysis included all EDR downloads with an event and with ignition cycles recorded at event and at download. There were 11,218 events that met these criteria. This dataset was called the persistence dataset. Using this data, the average number of ignition cycles between an EDR event and when the EDR was downloaded was calculated for non-related events.

Results

Event Analysis

In the event dataset, the CISS calculated Δv ranged from 1 km/h to 92 km/h, with an average CISS-reconstructed Δv of 19.3 km/h. CISS-reconstructed Δv at or below the EDR trigger threshold of 8 km/h made up 12% of the data. EDR downloads with no event present made up 7% of the total dataset and 56% of the data where CISS-reconstructed Δv was less than or equal to 8 km/h.

The percentage of vehicles that contained an EDR event are shown in Figure 1 grouped into 8 km/h bins. The percentage of older vehicles with an event at CISS Δv between 0 and 8 km/h was 70%. For newer vehicles subject to Part 563, the percentage of vehicles with an event present made up 80% of the data at CISS Δv between 0 and 8 km/h.

FIGURE 1 Percentage of vehicles with an event present on the EDR.

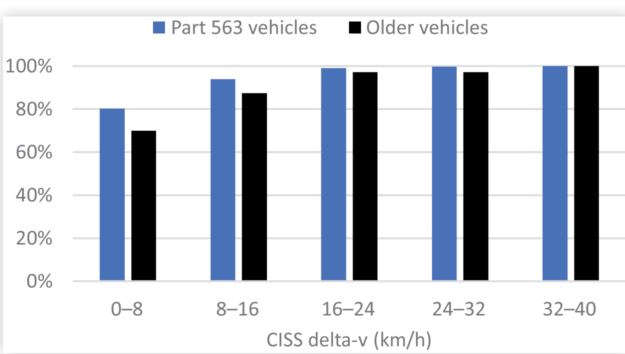

TABLE 3 Coefficients for the base logistic regression model.

Coefficients			p-value
Intercept	β_0	1.1638	<0.0001
Δv	β_1	0.1790	<0.0001
Back	β_2	−1.2947	<0.0001
Older	β_3	−1.0399	<0.0001
Missing	β_4	−0.6302	<0.0001
LTV	β_5	−0.3601	0.0114
Non-vehicle	β_6	−0.9284	0.0064

TABLE 4 Coefficients for the Toyota logistic regression model.

Coefficients			p-value
Intercept	β_0	2.8195	0.0187
Δv	β_1	0.2049	0.0004
Back	β_2	−2.5288	0.0024

The logistic regression models had an optimism corrected AUROC of 0.835 for the base model and 0.908 for the Toyota model. Accuracy for the base model was 77%. Accuracy for the Toyota model was 86%. Table 3 provides values for the base model logistic regression coefficients. Significant variables in the base model were Δv, rear impact, model year 2013 and newer, LTV vs car vehicle type, use of the missing vehicle algorithm in the CISS reconstruction, and impact with non-vehicle objects. For the Toyota model, the significant variables were Δv and rear impact. The coefficients for the Toyota model are shown in Table 4.

Results for the probability of an EDR event at a Δv of 8 km/h for the logistic regression models are presented in Tables 5 and 6. Probabilities at other Δv can be obtained using Equation 1 along with the β coefficients found in Tables 3 and 4.

Error Analysis

In the error analysis dataset, the average CISS-reconstructed Δv was 20.4 km/h. The average EDR Δv was 23.3 km/h. Within the CISS reconstructions, 9% of the cases had a Δv less than or equal to 8 km/h. Within the EDR data, 5% of the EDR reports had Δv equal to or below 8 km/h. Figure 2 shows EDR Δv compared to the corresponding CISS Δv.

In lower severity crashes, CISS reconstructions overestimated the EDR-reported Δv. For EDR-reported Δv between 0 and 16 km/h, CISS reconstructions overestimated EDR Δv by 11% on average. At EDR Δv of 16 km/h and higher, the CISS reconstructions underestimated the EDR Δv by −20% on average. Rear impacts had the lowest overall error with a −2.3% underestimate for the complete set, a 15.6% overestimate from 0 to 16 km/h, and a −4.8% underestimate from 16 km/h and higher. Non-vehicular

TABLE 5 Probability of EDR event at Δv of 8 km/h from base logistic regression model.

Base	Front/side	Front/side+older	Back	Back+older
Cars	93%	83%	79%	56%
LTV	90%	77%	72%	48%
Missing	**Front/side**	**Front/side+older**	**Back**	**Back+older**
Cars	88%	72%	66%	41%
LTV	83%	64%	58%	33%
Non-vehicle	**Front/side**	**Front/side+older**	**Back**	**Back+older**
Cars	84%	65%	59%	34%
LTV	79%	57%	50%	26%

TABLE 6 Probability of EDR event at Δv of 8 km/h from Toyota logistic regression model.

Toyota	Front/side	Back
All vehicles	99%	87%

impacts had the highest error of −31.3% for the complete set, a 19.6% overestimate from 0 to 16 km/h, and a −31.9% underestimate for 16 km/h and above. Linear regression results for all subsets are shown in Table 7.

Event Persistence

Non-related events on the EDRs refer to previously recorded events on the EDR that were not related to the crash investigated by CISS. Analysis of non-related events found a total of 720 events not related to the CISS-investigated crashes. The unrelated events had an average EDR-reported Δv of 10.2 km/h. For these unrelated events, 95% of the Δv were less than 20.2 km/h. The average number of ignition cycles from the time of the unrelated event to the time of download for the CISS-investigated crash was 3,766. The maximum number of ignition cycles between an unrelated event and CISS download was 49,964. Pre-2013 vehicles accounted for 159 of the unrelated events. The pre-2013 vehicles had an average of 4,366 ignition cycles between the unrelated event and CISS download, with a maximum of 49,964 ignition cycles. There were 561 vehicles model year 2013 or newer that had unrelated events. In these vehicles, there was an average of 3,595 ignition cycles between the unrelated event and CISS download, with a maximum of 25,142 ignition cycles.

Discussion

Reconstructed Δv data from the CISS database along with EDR downloads from the same source was analyzed using multivariate binary logistic regression to determine the probability of EDRs recording an event at the 8 km/h Δv threshold specified in Part 563. Vehicles manufactured by Toyota showed significantly higher probabilities compared to other manufacturers and were modeled separately due to this characteristic. The probability of an EDR event for Toyota vehicles at 8 km/h was 99% for frontal and side impacts and 87% for rear impacts. We did not find a significant difference in event probability at the trigger threshold when comparing pre-Part 563 Toyotas to Toyotas built after the Part 563 compliance date. Toyota vehicles also did not show significant differences

FIGURE 2 Error dataset EDR Δv compared to corresponding CISS Δv.

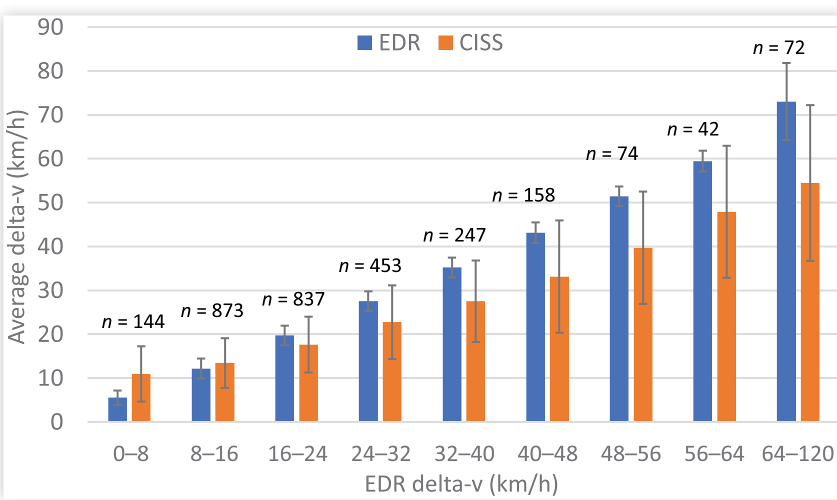

TABLE 7 Linear regression results.

Data group	Count	% of total	Slope	Error (%)	R^2	RMSE (km/h)	Min. CISS DV (km/h)	Max. CISS DV (km/h)	Avg. CISS DV (km/h)	Min. EDR DV (km/h)	Max. EDR DV (km/h)	Avg. EDR DV (km/h)
All	2,900	100%	0.818	−18.2%	0.874	8.5	3.0	92.0	20.4	1.9	113.1	23.3
All 0-16	1,017	35%	1.111	11.1%	0.823	6.0	3.0	51.0	13.1	1.9	16.0	11.2
All 16-UP	1,887	65%	0.798	−20.2%	0.89	9.1	4.0	92.0	24.4	16.0	113.1	29.7
New	2,209	76%	0.806	−19.4%	0.865	8.7	3.0	92.0	20.3	1.9	113.1	23.4
New 0-16	773	27%	1.09	9.0%	0.814	6.1	3.0	51.0	12.9	1.9	16.0	11.3
New 16-UP	1,440	50%	0.787	−21.3%	0.881	9.5	4.0	92.0	24.2	16.0	113.1	29.8
Old	691	24%	0.856	−14.4%	0.905	7.4	4.0	83.0	20.9	2.1	83.7	22.9
Old 0-16	244	8%	1.182	18.2%	0.853	5.6	4.0	34.0	13.7	2.1	16.0	10.9
Old 16-UP	447	15%	0.923	−7.7%	0.923	7.7	7.0	83.0	24.9	16.0	83.7	29.5
Front	2,164	75%	0.806	−19.4%	0.878	8.8	3.0	92.0	21.8	2.1	113.1	25.2
Front 0-16	638	22%	1.143	14.3%	0.816	6.4	3.0	51.0	13.7	2.1	16.0	11.4
Front 16-UP	1,528	53%	0.789	−21.1%	0.893	9.3	4.0	92.0	25.2	16.0	113.1	30.9
Side	399	14%	0.779	−22.1%	0.843	6.0	3.0	48.0	13.4	1.9	46.7	15.8
Side 0-16	232	8%	0.973	−2.7%	0.83	4.8	3.0	30.0	10.8	1.9	16.0	10.3
Side 16-UP	168	6%	0.725	−27.5%	0.872	6.8	5.0	48.0	17.0	16.0	46.7	23.3
Back	337	12%	0.977	−2.3%	0.89	7.6	5.0	90.0	20.0	3.1	71.0	19.9
Back 0-16	147	5%	1.156	15.6%	0.862	5.6	5.0	34.0	14.2	3.1	16.0	11.8
Back 16-UP	191	7%	0.952	−4.8%	0.902	8.7	8.0	90.0	24.5	16.0	71.0	26.1
CAR	1,682	58%	0.811	−18.9%	0.87	9.0	3.0	92.0	21.4	2.1	113.1	24.4
CAR 0-16	533	18%	1.156	15.6%	0.818	6.3	3.0	51.0	13.5	2.1	16.0	11.1
CAR 16-UP	1,151	40%	0.793	−20.7%	0.886	9.6	5.0	92.0	25.0	16.0	113.1	30.5
LTV	1,218	42%	0.83	−17.0%	0.882	7.6	3.0	83.0	19.1	1.9	73.9	21.7
LTV 0-16	484	17%	1.063	6.3%	0.832	5.6	3.0	35.0	12.6	1.9	16.0	11.3
LTV 16-UP	736	25%	0.807	−19.3%	0.899	8.4	4.0	83.0	23.4	16.0	73.9	28.6
Damage	1,690	58%	0.79	−21.0%	0.902	7.7	5.0	90.0	21.2	1.9	113.1	25.3
Damage 0-16	506	17%	1.064	6.4%	0.853	5.2	5.0	35.0	12.9	1.9	16.0	11.4
Damage 16-UP	1,186	41%	0.776	−22.4%	0.913	8.3	5.0	90.0	24.7	16.0	113.1	31.2
Missing	1,210	42%	0.879	−12.1%	0.834	9.3	3.0	92.0	19.4	2.1	95.0	20.4
Missing 0-16	511	18%	1.159	15.9%	0.801	6.7	3.0	51.0	13.3	2.1	16.0	11.1
Missing 16-UP	701	24%	0.847	−15.3%	0.853	10.3	4.0	92.0	23.8	16.0	95.0	27.2
V2V	2,751	95%	0.837	−16.3%	0.882	8.0	3.0	92.0	20.1	1.9	113.1	22.5
V2V 0-16	992	34%	1.109	10.9%	0.826	6.0	3.0	51.0	13.0	1.9	16.0	11.3
V2V 16-UP	1,763	61%	0.816	−18.4%	0.899	8.6	4.0	92.0	24.0	16.0	113.1	28.8
NONV	149	5%	0.687	−31.3%	0.835	13.1	5.0	83.0	27.5	2.9	99.0	37.3
NONV 0-16	25	1%	1.196	19.6%	0.71	8.8	5.0	35.0	14.7	2.9	14.5	10.7
NONV 16-UP	124	4%	0.681	−31.9%	0.846	13.6	5.0	83.0	30.1	16.1	99.0	42.6

for car vs LTV, WinSmash damage vs missing algorithm, or non-vehicle impacts. The high probabilities of an event at 8 km/h for Toyota manufactured vehicles is an indication that these vehicles have a trigger threshold lower than 8 km/h.

For other manufacturers, the modeling showed a significant increase in probability at the 8 km/h threshold for model year 2013+ vehicles subject to the Part 563 standard when compared to older vehicles. For non-Toyota Part 563-compliant vehicles in frontal or side impact, the probability of an event at 8 km/h or lower was 90%–93%. The rear impact probability at 8 km/h or lower ranged from 72% to 79% for non-Toyota Part 563-compliant vehicles. Pre-Part 563 non-Toyota vehicles had probabilities between 77% and 83% for frontal and side impacts. Rear impact probabilities for pre-Part 563 vehicles ranged from 48% to 56%. Use of the WinSmash missing vehicle algorithm reduced the probability of an EDR event at a CISS-reconstructed Δv of 8 km/h or lower. Non-vehicle impacts also had lower probability of an EDR event at the 8 km/h threshold with CISS-reconstructed Δv. For non-Toyota vehicles, cars had higher probabilities of an event at the 8 km/h trigger threshold than LTVs.

Error analysis was performed for a dataset containing 2,900 cases in which there was a CISS-reconstructed Δv as well as an EDR-reported Δv. This dataset contained frontal, side, and rear impacts. For the complete dataset CISS reconstructions underestimated EDR Δ*v* by −18.2% on average. At EDR Δ*v* of 16 km/h and lower, the CISS reconstructions overestimated the EDR Δ*v* by 11.1% on average. At EDR Δ*v* of 16 km/h and higher, the CISS reconstructions underestimated the EDR by −20.2% on average.

Frontal impacts were underestimated by −19% for the complete spectrum of Δ*v*. This underestimate is consistent with the findings of previous authors studying reconstructed frontal impacts in NASS and CISS [7, 9]. Frontal impact reconstructions in CISS overestimated the EDR Δ*v* by 14.3% at EDR Δ*v* of 16 km/h and lower. At EDR Δ*v* of 16 km/h and higher, frontal impact reconstructions underestimated the EDR by −21.1%.

In rear impacts, EDR Δ*v* was underestimated by −2.3% for the complete spectrum of Δ*v*. In rear impact reconstructions, CISS overestimated the EDR Δ*v* by 15.6% at EDR Δ*v* of 16 km/h and lower. At EDR Δ*v* of 16 km/h and higher, CISS rear impact reconstructions underestimated the EDR by −4.8%. Previous studies have shown higher percent error for frontal impact compared to rear impact, but not as a direct comparison in the same study [5, 8].

In side impacts, CISS reconstructions underestimated EDR Δ*v* by −22.1% overall. Using a 16 km/h cutoff, side impacts at lower Δ*v* underestimated the EDR by −2.7% and underestimated by −27.5% at higher Δ*v*. Reducing the cutoff by 2 km/h resulted in a 2.1% overestimate at EDR Δ*v* 14 km/h and lower and a −25.8% underestimate at 14 km/h and above. We believe this is the first study of reconstructed Δ*v* compared to EDR Δ*v* for side impacts.

Reconstructions using the WinSmash missing vehicle algorithm had lower error over the entire range of Δ*v* compared to reconstructions using direct damage; however, the missing vehicle cases had higher overestimates compared to the EDR at Δ*v* less than 16 km/h. At 16 km/h and below, cases using the WinSmash damage method overestimated EDR Δ*v* by 6.4% while cases using the WinSmash missing vehicle method overestimated by 15.9%. The overestimate of Δ*v* in CISS reconstructions using the missing vehicle algorithm is consistent with the lower probability that these cases have an EDR event at a CISS-reconstructed Δ*v* of 8 km/h.

Non-vehicle impact reconstructions had the highest magnitude of error across the full spectrum of Δ*v*, underestimating the EDR Δ*v* by −31.3% on average. At 16 km/h and below, these cases had the highest overestimate as well, at 19.6%. From 16 km/h and higher, these reconstructions underestimated the EDR by −31.9%. The overestimate of Δ*v* in CISS reconstructions of non-vehicle impacts in the range of Δ*v* less than 16 km/h is consistent with the lower probability of these cases having an EDR event at a CISS-reconstructed Δ*v* of 8 km/h.

The trend of CISS overestimating the EDR at lower Δ*v* and underestimating at higher Δ*v* was found in all subsets of data. In all subsets except side impacts, a split at 16 km/h showed the over/underestimate trend. For side impacts, the over/underestimate trend was present with a split at 14 km/h. The linear regressions show average error over a range of Δ*v*. The data contains scatter with some individual data points overestimating the EDR and some underestimating the EDR at any given Δ*v*. This means that a correction factor cannot be simply applied to the CISS Δ*v* to obtain a better estimate. With CISS reporting a higher Δ*v* in the range of the Part 563 trigger threshold, the EDR event probabilities calculated in the logistic regressions can be considered underestimates.

Prior to Part 563, logic for retaining event data was not specified in a federal requirement. Some early EDRs manufactured before Part 563 overwrote non-deployment events after a limited number of ignition cycles. In those vehicles it was possible for an EDR to have recorded a non-deployment event and then erase it after a short period of time. The recording logic of Part 563 means that if a vehicle has experienced an event that reached the trigger threshold, it will be stored on the EDR. Rather than being erased due to a number of ignition cycles, an event can be overwritten by another event. Events that met the trigger threshold and occurred prior to the CISS-related crash were stored on the EDRs. In CISS, these are referred to as unrelated events. The unrelated events on the EDRs had an average EDR-reported Δ*v* of 10.2 km/h. A study of average daily ignition cycles found that non-commercial vehicles had an average of 6 to 7 ignition cycles per day [15]. In the present study, non-related events on the EDRs had an average of 3,766 ignition cycles. Using 6.5 ignition cycles per day, the average non-related event predated the subject collision by 1.6 years.

A limitation of this study is the reliance on CISS-reconstructed Δ*v*. As EDRs do not record a Δ*v* when an event is not recorded, EDR Δ*v* cannot be used to model event probability. Δ*v* reconstructed by CISS differs from Δ*v* recorded by EDRs. In the range of the EDR trigger threshold, CISS-reconstructed Δ*v* overestimates EDR Δ*v* on average. The overestimate of Δ*v* in the range of the Part 563 trigger threshold causes an underestimate of EDR event probability. The probabilities calculated in this study are applicable to vehicles that are equipped with EDRs. Older vehicles without EDRs or vehicles with EDRs not accessible to CISS are not represented in the study.

Conclusions

The purpose of Part 563 is to help ensure that EDRs record, in a readily usable manner, data valuable for effective crash investigations and for analysis of safety equipment performance. The entire spectrum of crash severity is important in different types of analysis, including analysis of injury risk. It is for this reason that the CISS crash database is designed to cover the entire spectrum of Δ*v*. The EDR trigger threshold set at a Δ*v* of 8 km/h ensures that EDR data captures the low end of the crash severity spectrum. Vehicles built after the Part 563 compliance date have higher probabilities of capturing low speed events on the EDR. This is an indication that the Part 563 trigger threshold is effective in increasing the amount of EDR data available for accident reconstruction and safety research. The persistence of these events on the EDR up to years after the event allows the use of EDR data well after the crash has occurred. The results of this study provide information on the field performance of EDRs valuable to researchers, manufacturers, regulatory bodies, and personnel working in the field of accident reconstruction. Prior to the Part 563 compliance date, no trigger threshold or data retention for non-deployment events was specified. The high probability of events present on the EDR at the 8 km/h trigger threshold is an indication that the Part 563 trigger threshold has been incorporated into EDRs and is an indication that an EDR may contain crash information whether or not an airbag deployment has occurred. The high probability of Part 563-compliant EDR images containing an event at the 8 km/h trigger threshold provides an additional data point for personnel performing accident reconstruction when the EDR download does not contain an event.

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