

A SYSTEMS MODELING METHODOLOGY FOR ESTIMATION OF HARM IN THE AUTOMOTIVE CRASH ENVIRONMENT

Alexandra C. Kuchar

Volpe National Transportation Systems Center, USDOT

USA

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ABSTRACT

A systems modeling approach is presented for assessment of harm in the automotive crash environment. The methodology consists of parametric simulation of several controlled accident variables, with case results weighted by the relative frequency of each specific event. A hierarchy of models is proposed, consisting of a statistical model to define the crash environment and assign weighting factors for each crash situation case, and vehicle models for 3-dimensional kinematic simulation of crash events. Approximating functions are utilized to estimate occupant harm metrics based on vehicle crash response. Head and chest injury results for each case are converted to harm vectors, in terms of probabilistic Abbreviated Injury Scale (AIS) distributions based on previously defined risk analyses. These harm vectors are weighted by each case's probability as defined by the statistical model, and summed to obtain a total estimate of harm for the crash environment. The methodology is applied to a subset impact environment consisting of single- and two-vehicle frontal collisions among passenger cars and light trucks. The model is validated against injury field data, and is found to accurately reflect trends in distribution of injury severity. The model is also exercised for variable sensitivity analyses, wherein changes in light truck/car population mix and other parameters are evaluated in terms of their effect on occupant harm within the subset crash environment.

1.0 Introduction

This paper presents a systems modeling approach for evaluation of overall safety in the automotive fleet. This methodology stands in contrast to typical approaches, where specific safety issues such as air bags are addressed independently. However, the recent surge in light truck sales in the U.S. has led to the advent of a broader problem: how to evaluate the aggressivity of these larger passenger vehicles in two-vehicle accidents while also considering their potential safety benefits in single-vehicle crashes. While light truck vehicles do provide added protection to occupants within the vehicle, one recent statistical study reports that light trucks are so aggressive due to both mass and geometry that in head-on crashes between cars and light trucks, deaths in the cars outnumber those in the light trucks by 70% (Joksch, 1998). The systems model methodology applied here features computational vehicle models to represent cars

and light trucks, making it suitable for analysis of aggressivity and compatibility among dissimilar vehicles.

This paper describes a systems modeling methodology for prediction of passenger injuries across the entire accident environment, considering a variety of metrics including vehicle type, impact speed, occupant size, safety belt usage, and other factors which directly affect overall safety. This approach will allow for evaluation of global effects of small changes to the accident environment, so that proposed automotive safety regulations may be evaluated in terms of their total safety benefit. The methodology has been developed as a generalized tool for assessment of a variety of crashworthiness topics, such as air bags and vehicle design characteristics. The methodology is applied here to study vehicle aggressivity in terms of the relationship between passenger vehicle fleet mix and overall harm.

History. Several previous studies have considered a systems approach for investigating vehicle safety. During 1975-78, the Ford Motor Company developed the Safety Systems Optimization Model (Ford Motor Co., 1978), featuring a simulation-optimization program for maximizing a single vehicle's safety performance in frontal crashes. The same program was substantially modified by the University of Virginia in the early 1980s (White, et al., 1985), to include new biomechanical transforms and updated accident data as well as multivariate analysis capability. This model utilized approximating functions to estimate relationships between crash variables due to limitations in computational power at the time. Other motor vehicle manufacturers, including Fiat and Volkswagen, have also developed programs for optimizing vehicle design for crashworthiness, with emphasis on single-vehicle as opposed to fleet wide performance.

The model presented here differs from these earlier models in several aspects. It predicts total harm over a range of vehicle types rather than a single subject vehicle. While the model estimates injuries over a given set of crashes, it does not include an optimization algorithm for minimization of total harm. The model considers air bags in addition to seat belts, and occupants of varying size. It also incorporates recent accident statistics and more sophisticated biomechanical transforms than earlier approaches. An earlier application of the methodology was presented to describe the modeling approach and initial validation (Kuchar, 2001). This paper presents an

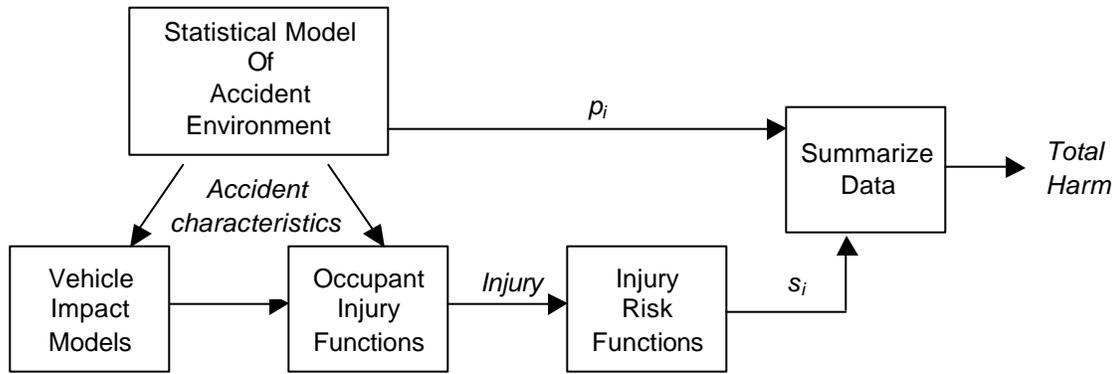


Figure 1. Fleet Systems Model Methodology

updated application of the model, with more recent crash statistics, approximating functions to estimate occupant injury as a function of vehicle crash pulse, and consideration of non-air bag equipped vehicles.

Governing Equation and Methodology. The methodology is based upon the following governing equation for estimation of total injuries:

$$Harm = \sum_i p_i s_i \quad (1)$$

Each i is a specific crash event, defined in terms of assigned values for model variables, such as vehicle type, restraint usage and occupant size. The accident environment is described by the range of i , which may include as few or as many cases as desired. p_i is the probability of each event i , its expected rate of occurrence based on accident statistics. s_i is the expected injury outcome of crash event i , represented in terms of probable levels of harm as measured by the Abbreviated Injury Scale (AIS). Each case's expected harm outcome s_i is determined via computer simulation of vehicle crashes and numerical approximation of occupant kinematics. This formulation allows for consideration of a range of accidents, while assigning an appropriate weight to each event based upon field data. Given this methodology, the model's robustness is directly related to all three of these factors: the number and range of accidents considered, the reliability of the accident field data, and the accuracy of the computational models.

Figure 1 graphically depicts the implementation of the methodology. The term "Fleet Systems Model" refers to the whole system, which consists of a family of models. There are statistical models to describe the accident environment, vehicle structural crashworthiness models to predict vehicle behavior, occupant kinematic models to simulate dummy motion, and injury risk functions for estimation of harm.

2.0 Statistical Model of Accident Environment

The motive for examination of accident field data for development of a statistical model is threefold: to select and

define the boundaries of the model environment, for case weighting (computation of p_i for each case), and to provide a set of validation data against which the model's estimates of total injury are compared.

Subset Environment. A review of past year crash statistics is performed to identify the boundaries of the model environment - the subset of the real crash environment to be represented within the model. By identifying those events that are most frequent and lead to the greatest number of injuries, the model's coverage of the real environment can be maximized for a given number of cases.

The annual distribution of passenger vehicles in single- and two-vehicle towed accidents by impact mode and severity outcome is given in Table 1. Severe crashes are defined as those in which at least one occupant sustains an injury of AIS 3 or higher.

Table 1. Vehicles in Towed Crashes, by Accident Mode, 1994-99¹

Crash Mode	All Crashes (n=3.45 million vehicles/year)	Severe Crashes (n=93,000 vehicles/year)
Single Vehicle		
Fixed Object,		
Frontal	6.7%	13.5%
Rollover	6.1%	19.1%
Other	11.3%	12.6%
Two Vehicle		
Head-on	2.7%	11.9%
Side Impact	45.1%	33.6%
Rear	19.8%	4.6%
Sideswipe	5.7%	2.9%
Other	2.5%	1.6%

¹ All accident field data presented are obtained from the NHTSA National Automotive Sampling System (NASS) Crashworthiness Data System (CDS) database, years 1994-99.

Note that vehicles in frontal accidents comprise a large percentage of severe crashes: 13.5% of these vehicles are in frontal single-vehicle impacts, while 11.9% are in two-vehicle head-on accidents for a total of 25.4% of all vehicles in towed accidents. Side impacts are more common, accounting for 45.1% of vehicles in all crashes and 33.6% of vehicles in severe crashes. Single-vehicle rollover accidents also comprise a large percentage of vehicles in severe crashes, at 19.1%. Because current frontal vehicle crashworthiness models are more feasible for parametric simulation than side impact models, the application of the methodology presented here considers only frontal impacts. This includes all single- and two-vehicle frontal impacts among cars and light trucks. Furthermore, while the vehicle crashworthiness models employed here simulate full frontal impacts, they are also assumed to approximate angled and offset crashes.

The same methodology is applied to select other parameters of the subset crash environment, wherein emphasis is placed on the frequency and severity outcome of impact variables, as well as modeling feasibility of impact parameters. For example, vehicle type is limited to passenger vehicles under gross vehicle weight of 4550 kg (10,000 lbs.), while all other vehicle groups such as buses and motorcycles are excluded. The passenger vehicle population is modeled as two separate classes, cars and LTVs (including all light trucks, sport utility vehicles, vans and minivans). Occupant seat position is limited to front seat driver and passenger occupants only, as this group represents over 86% of all occupants in towed crashes. For estimation of harm in each simulated case, only injuries to the head and chest are considered, as these body areas are by far the most common region of serious injury in frontal collisions.

Given this parametric definition of the subset environment, it represents a total of 335,000 vehicles in towed accidents per year, 24,000 of which feature an occupant sustaining a severe injury.

Computation of Case Weights p_i . The p_i term of the governing equation is a function of several accident variables:

$$p_i = fn(mode, vehicle, speed, belt usage, air bag deployment, seat position, occupant size) \quad (2)$$

Each unique permutation of these variables defines a single case within the methodology, and the sum of all of these cases describes the entire subset environment considered. For each variable, the relative probability of each value is determined from field data. Some interdependencies exist among these six variables, as illustrated in Figure 2. The first and only probabilistically independent simulation parameter is accident mode, which determines the relative probability of each vehicle type. Both impact mode and vehicle type determine weighting of each simulated vehicle impact speed. Vehicle type alone determines seat distribution, which in turn defines the probabilities of the occupant size and seat belt usage variables. For the range of accident years considered (1992-97), air bags were made

available in new vehicles in a piecemeal basis: first drivers, then passengers; in cars before LTVs. Therefore, airbag availability is modeled statistically as a function of both vehicle type and seat position. The numbers in parenthesis in Figure 2 indicate the number of permutations for each variable. This yields a total of 1008 cases, obtained via perturbation of 2 vehicle types, 2 impact modes (single- and two-vehicle impacts), 2 partner vehicles (car and LTV) in one of the impact modes (two-vehicle impacts), 7 impact speeds, 3 occupant sizes, 2 occupant locations, 2 seat belt configurations, and 2 air bag availability settings.

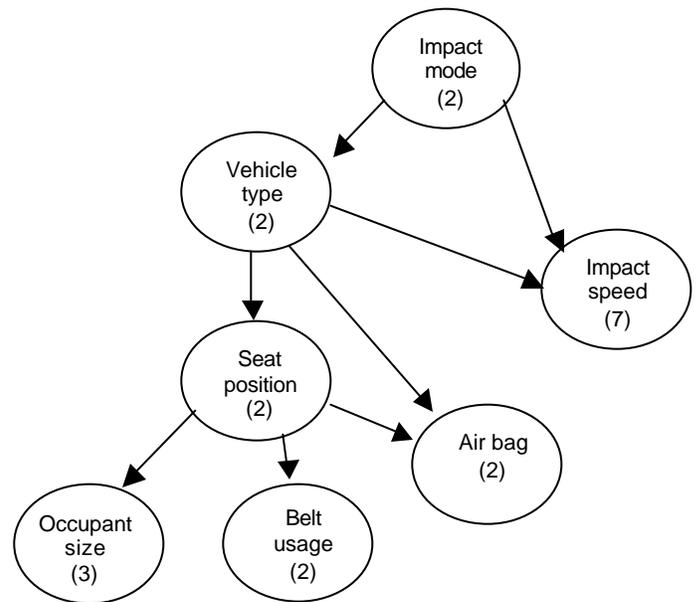


Figure 2. Hierarchy of Dependencies Among Probabilities of Simulation Variables

For variables with discrete values (such as seat belt usage, yes or no), linked probabilities are derived directly from field data. For continuous variables such as vehicle speed and occupant size, probability density functions (PDFs) are defined, and relative probabilities of each value are computed via integration. Impact speeds for case simulation are selected to emphasize severe accidents, but are weighted according to frequency across all accidents.

The statistical model of the subset environment provides the data for computation of p_i for each case in terms of the linked probabilities depicted in Figure 2.

$$p_i = p(mode) \times p(vehicle|mode) \times p(speed|vehicle, mode) \times p(seat\ position|vehicle) \times p(occupant\ size|seat\ position) \times p(belt\ usage|seat\ position, vehicle) \times p(air\ bag|seat\ position, vehicle) \quad (3)$$

Note that the computed value of p_i for each case should be very small, given that there are a total of 1008 cases evaluated for the subset environment, and the sum of all p_i must equal 1.

3.0 Vehicle Crashworthiness Simulation Models

Vehicle response for each case is simulated using computational models of vehicles in frontal impacts. The vehicle models are one dimensional lumped-parameter systems, with three discrete masses representing the Occupant Compartment, Engine, and Wheels. Six non-linear springs represent energy-absorbing load paths in the front end of the vehicle, and are defined to approximate various buckling and crushing modes during frontal impacts. Each spring is described in terms of a segmented force-deflection curve to represent static behavior, plus a dynamic magnifier component, which applies dynamic force as a function of the spring's strain rate and static characteristics.

The models are simulated and developed using the SISAME (Structural Impact Simulation And Model Extraction) program (Mentzer, 1999), which performs forward simulation of one-dimensional lumped-parameter models, and features an optimization tool for the development of these models. This model extraction-optimization approach has been proven for development of highly accurate 1-dimensional models of vehicles in full frontal impacts (Mentzer et al., 1992). More recent developments in the SISAME program enable multiple-event extraction of simulation models, where crash test data from more than one event may be used to identify an optimal simulation model.

The passenger car fleet is represented by a single vehicle model based on a 1995 Chevrolet Lumina and the LTV fleet is represented by a model of a 1995 Ford Explorer. Future development of the methodology will include additional vehicle models to represent multiple weight classes of cars and LTVs, as well as more geometrically detailed vehicle models to capture 3D effects such as bumper mismatch. However, for initial validation of this systems approach, the 1-dimensional full frontal crashworthiness models are considered adequate for this application. Each model is extracted from two full frontal crash tests conducted at different speeds (24 and 56 kph for the car, and 48 and 56 kph for the LTV). Both models demonstrate very good correlation with test data at both impact speeds. No test data was available for validation of the models in vehicle-to-vehicle impacts.

The models are simulated in single- and two-vehicle full frontal impacts at 7 different impact speeds to generate occupant compartment response data for input into occupant injury approximating functions.

4.0 Occupant Approximating Functions

A previous application of this methodology consisted of full MADYMO simulation of 504 occupant cases to predict occupant head and chest injury. Because full parametric simulation of such a large number of cases becomes cumbersome for the number of desired occupant cases (1,008 for the application presented here), approximating functions were developed to estimate occupant injury from vehicle crash pulse parameters. Linear regression analyses were performed on occupant injury results from NHTSA NCAP and FMVSS208 full vehicle compliance tests

as well as occupant simulation results from existing MADYMO models. Input parameters consisted of 5 descriptive crash pulse characteristics, including delta-v, peak acceleration, time of peak acceleration, peak displacement, and time of peak displacement. Three distinct approximating functions for estimating HIC, peak chest acceleration and peak chest deflection were developed for each occupant configuration (characterized by vehicle type, occupant size, occupant position, seat belt usage and air bag availability). The chest injury metrics were treated as pure linear functions across all input observations. Because the known HIC observations clearly reflected an exponential nature as a function of impact speed, $\ln(\text{HIC})$ is estimated by the approximating functions.

These functions developed via linear regression on crash pulse parameters demonstrate excellent correlation with known data. It should be noted however that these functions are rather heuristic in nature, generally based on single-point crash tests and computer simulation. Furthermore, in the absence of computer simulation results for non-air bag equipped occupant scenarios, the target results were estimated from scaled injury parameters obtained from air bag simulation cases. Nonetheless, the approximating functions give a good general estimate of head and chest injury for a wide variety of occupant scenarios, and provide accurate trend behavior comparable to that of parametric simulation.

5.0 Biomechanical Models

Because the vast majority of serious injuries in crashes are the result of head and chest trauma, only head and chest injury metrics are used here to measure occupant harm. Further refinement of the methodology may consider other injury mechanisms, such as neck and femur loads.

Head Injury Criterion (HIC) is computed from triaxial head acceleration response from each occupant simulation case. Chest injury for each simulation case is measured in terms of the Combined Thoracic Index (CTI), defined as

$$CTI = \frac{A_{max}}{A_{int}} + \frac{D_{max}}{D_{int}} \quad (4)$$

where A_{max} and D_{max} are peak values observed during simulation and A_{int} and D_{int} are constants defined for each dummy size. CTI is not currently used as a regulatory criterion, though it is recommended by the National Highway Traffic Safety Administration (NHTSA) for research use (Kleinberger, et al., 1998).

Because both HIC and CTI are computed from a controlled environment - direct measurements of acceleration, deflection, or force during crash tests or computer simulation - they are not obtainable from field data. Injuries in real crashes are recorded in terms of the Abbreviated Injury Scale (AIS), which is less precise than the standard injury criteria. Nonetheless, the AIS scale is the only source of injury data available from the field, and

provides the validation data for comparison of injury results computed by the Fleet Systems Model.

A series of mathematical models to convert HIC and CTI into the AIS scale are presented in Figures 3 and 4, commonly known as injury risk functions (Eppinger et al., 1999). These functions are proposed by NHTSA based on experimental data and previous research to estimate harm from measured criteria. The HIC injury risk functions are log normal approximations, while the CTI curves are two-parameter Weibull approximations. Both sets of curves are based upon experimental tests within the regulatory range of interest ($HIC=1000$, $A_{max}=60G$ and $D_{max}=76mm$), and therefore these approximations are more heuristic for higher injuries. The AIS=6 curve shown below for CTI is not proposed by NHTSA, but has been extrapolated for use within this study.

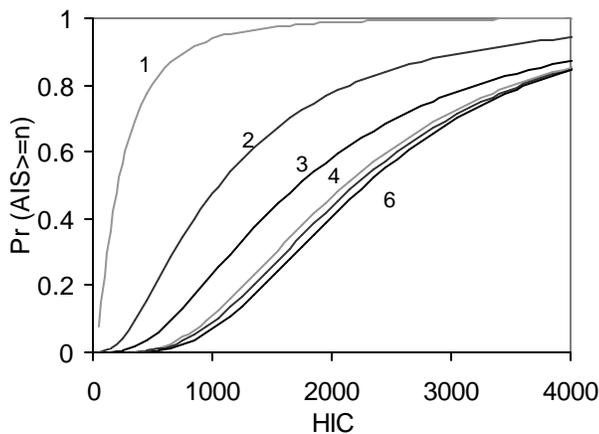


Figure 3. Injury Risk Functions for HIC
(from Eppinger, et al., 1999)

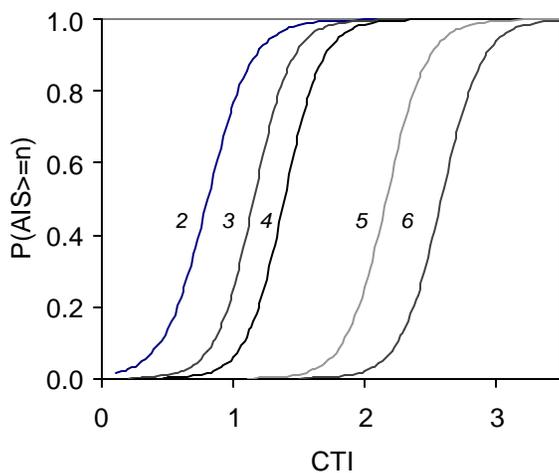


Figure 4. Injury Risk Functions for CTI
(from Eppinger, et al., 1999)

Applying these functions provides a mathematical transform for conversion of HIC or CTI into probabilities of each AIS result. Hence, the injury risk functions can be applied to obtain the probabilities of AIS=0,1,2,3,4,5, and 6.

These values correspond to a vertical "slice" through Figure 3 or 4 at a given injury value. For each HIC and CTI computed from simulation, a vector of AIS probabilities is computed, corresponding to that occupant's probability of sustaining head or chest injuries corresponding to each AIS state. There are therefore two harm vectors obtained from each occupant simulation, one for head injuries (HIC) and the other for chest injuries (CTI). For each occupant simulation, the head and chest harm vectors are each multiplied by a normalized cost function, which quantifies the relative harm of each AIS level (NHTSA, 1999). The vector resulting in greater computed harm is assigned to be the vector s_i , or probabilistic AIS outcome, for that simulation case.

6.0 Fleet Systems Model Results

Parametric simulation of the vehicle models and application of the occupant approximating functions yields a total of 1,008 individual cases. For each of these cases there is a probability value (p_i) obtained from the statistical model and a harm vector (s_i) obtained from vehicle, occupant, and biomechanical models. These quantities are multiplied and summed according to the governing equation (1) to yield an estimated distribution of injuries for the subset environment.

The computed AIS distribution for the entire subset environment is shown in Figure 5, compared against field data. Because non-injuries and minor injuries of AIS 0,1, and 2 comprise the vast majority of the results, and because severe injuries of AIS 3 and higher are of greatest interest, only serious injuries are plotted, with minor injury figures given in text. A total annual number of 427,000 occupants is represented, so 1% of the environment corresponds to roughly 4,270 occupant injuries.

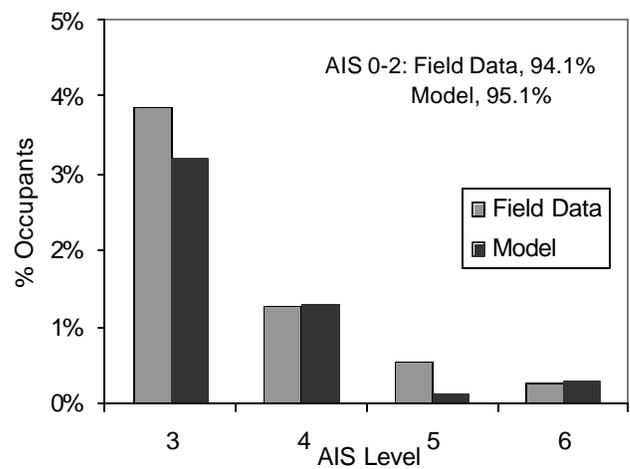
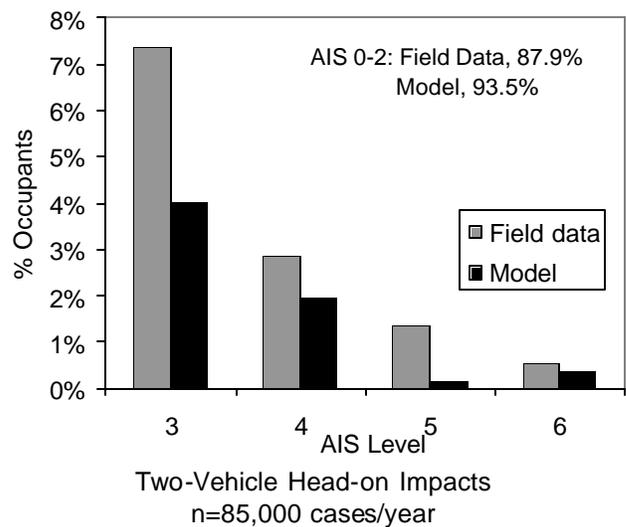
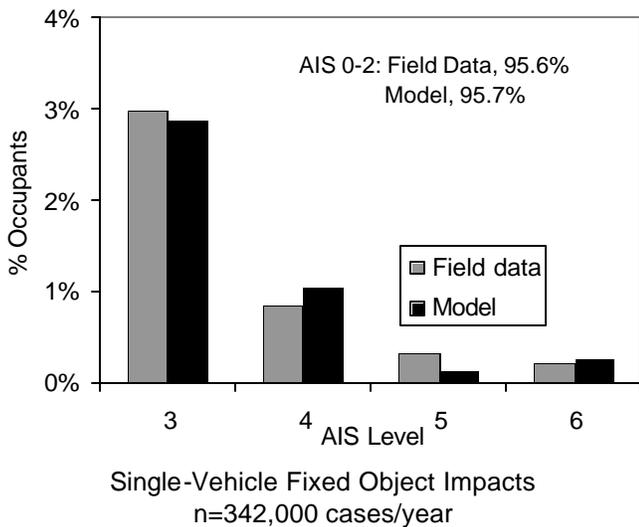


Figure 5. AIS Distribution of Subset Environment Model vs. Field Data Comparison

The model demonstrates very good agreement with field data. The model nearly perfectly predicts the percentage of AIS 4 and 6 injuries within the frontal crash environment. The model underestimates AIS 5 injuries by 0.5% of all occupants, with an underestimation of about 0.8% among AIS 3 injuries. Improvement of the model's accuracy in predicting AIS 5 injuries would likely result in a cumulative



Figures 6 and 7. AIS Distribution by Impact Mode

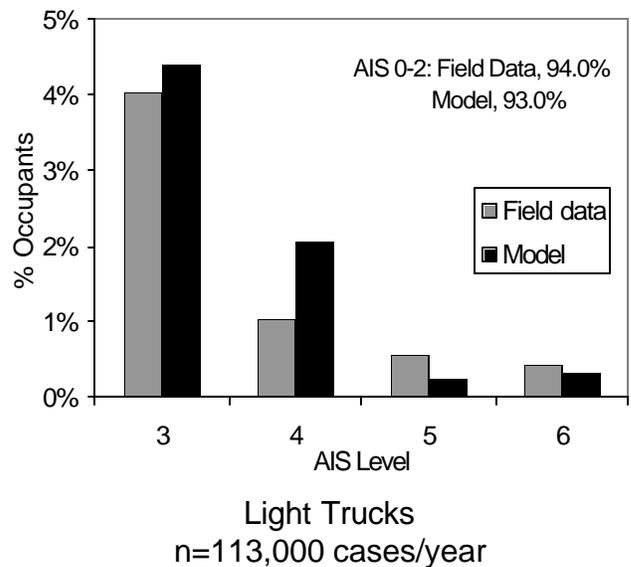
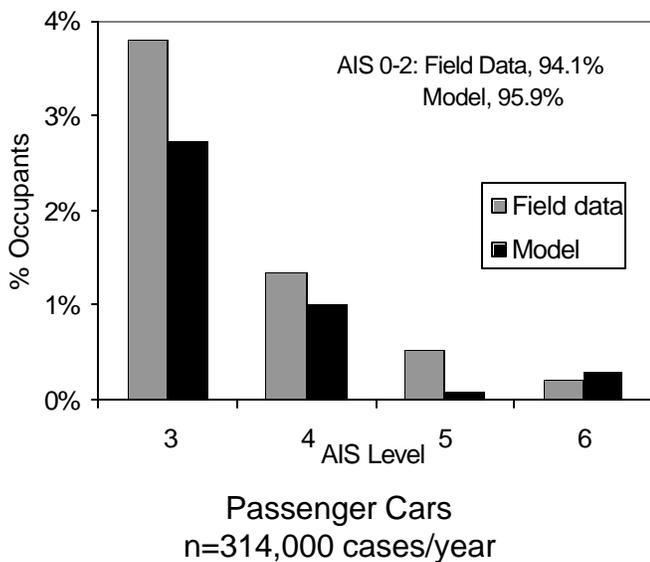
shift of injuries across the AIS 4 category. Nonetheless, the data clearly shows very good agreement when compared against field data from crash statistics.

In Figures 6 and 7, the model results and field data are presented by impact mode, so that the model's accuracy within each of these groups may be assessed. Figure 6 shows very good agreement with field data among occupants in single-vehicle fixed object crashes. Figure 7 shows the methodology is fairly accurate for predicting 2-vehicle head-on impacts, though the model's tendency to underrepresent AIS 3 and 5 injuries is evident.

Figures 8 and 9 show the same data sorted by vehicle type, car and LTV. For car impacts (Figure 8), the model appears to closely estimate injuries for AIS 4 and 6,

with an underestimation of injuries in the AIS 3 and 5 categories. Among LTV impacts, the model appears to closely predict the severest injuries of AIS 5 and 6, while overestimating AIS 3 and 4 injuries 1.0% and .4%, respectively.

Although the model shows less accurate prediction of injury distribution among LTV occupants than car occupants, the number of cases represented in Figure 9 is also much smaller, at n=113,000. Therefore, in terms of the absolute number *n* of injuries, the model results are roughly equally accurate for LTV and car impacts. This suggests that larger percentage errors may be acceptable for smaller subsets of data, when absolute numbers of injuries are considered. For the methodology to accurately reflect



Figures 8 and 9. AIS Distribution by Vehicle Type

the entire fleet, however, it is highly desirable to accurately predict occupant injury in all types of vehicles. The small predictive errors observed in Figures 8 and 9 may therefore highlight some areas for potential improvement of the model results. One source of error may be a systematic tendency within the vehicle models or occupant approximating functions to underestimate severe (AIS 5 and 6) injuries while overestimating moderate (AIS 3 and 4) injuries. Although these LTV models have been validated at 56 and 48kph (35 and 30mph), they have been extrapolated to simulate higher initial speeds of up to 80kph (50mph), where the most severe injuries are likely occur. Refinement and validation of the LTV occupant approximating functions at higher speeds may address this issue, although validation data from high speed crash tests are not currently available for cars or LTVs.

Vehicle Aggressivity Analysis. To assess the role of vehicle aggressivity and compatibility within the model environment, serious injury results of only 2-vehicle impacts between LTVs and cars are shown in Figure 10. This subgroup of cases represents roughly 7.8% of the modeled crash environment, or roughly 33,000 occupants annually, 5,000 of which are seriously injured. The y-axis scale in Figure 10 represents only the percentage of occupants involved in LTV-car impacts (where 100% reflects 33,000 occupants). The data demonstrates that car occupants undergo significantly more numerous and more severe injuries than their LTV counterparts. AIS 3 and 4 injuries in cars outnumber those in LTVs by roughly 2 to 1 and 3 to 1 in each category, respectively. While small numbers of AIS 5 and 6 injuries are predicted for car occupants, even fewer injuries are predicted for LTV occupants in LTV/car collisions: fatalities in cars during car/LTV impacts outnumber those in LTVs by roughly 4 to 1. The data therefore shows a clear disadvantage for car occupants. The mass and stiffness incompatibility between these vehicles is highlighted by the simulated crashworthiness behavior in the vehicle models. For example, the maximum approach speed simulated for 2-vehicle

collisions is 78 kph per vehicle, or an approach speed of 156 kph. Due to the differences in the two vehicles' mass and stiffness, the LTV undergoes a delta-v of only 90 kph (including rebound effects) at this highest impact speed, whereas the car has a much higher delta-v of 107 kph. Because the vehicle models are 1-dimensional mass/spring representations of vehicles, this simulated behavior reflects vehicle incompatibilities due to vehicle mass and stiffness but not geometry.

As LTVs continue to gain popularity as passenger vehicles, their potential effect on total safety within the accident environment grows in importance. To study the net safety effects of increasing LTV population within the accident environment (or the frontal impact environment, as the methodology covers here), the model was exercised to assess the sensitivity of occupant injuries as a function of LTV/car fleet mix. Occupant injuries were predicted for the hypothetical cases of a 100% car fleet and a 100% LTV fleet, as well as a range of scenarios in between these endpoints, at 10% intervals. The predicted results for serious injuries are shown in Figure 11. This study assumes that the total number of vehicles in the fleet remains fixed. The results reflect all single- and two-vehicle frontal impacts involving cars and LTVs. A reference line indicates the 1994-99 baseline environment, consisting of roughly 27% LTVs, 73% cars.

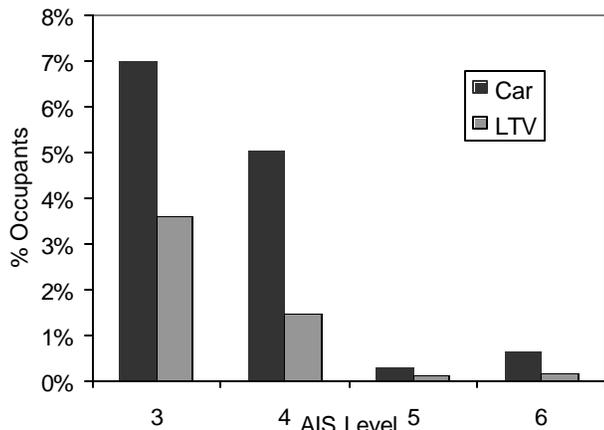


Figure 10. Serious Injuries in LTV/Car Impacts, by Subject Vehicle

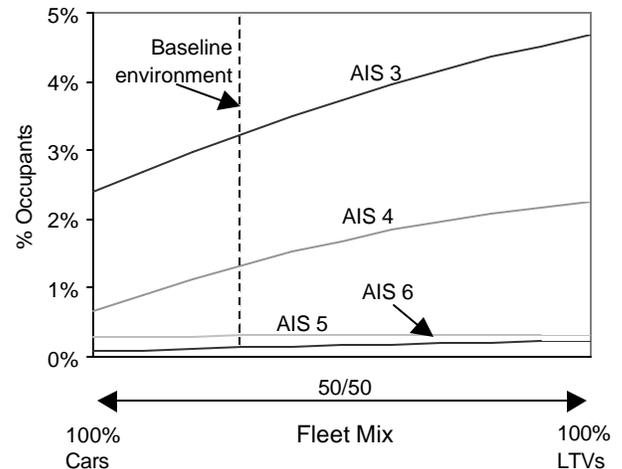
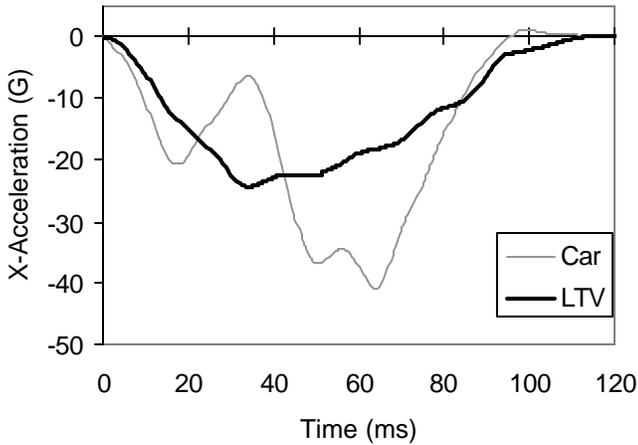
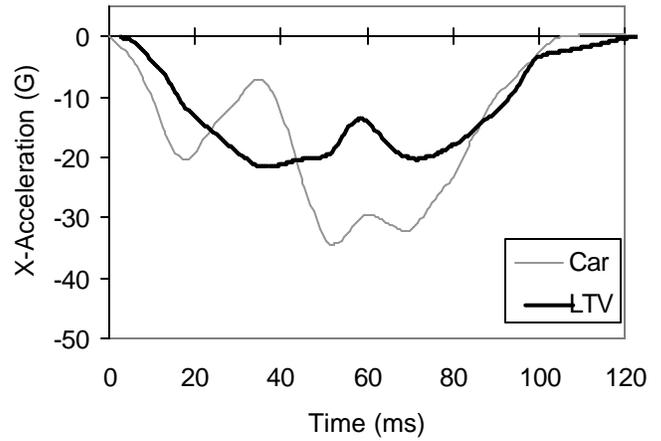


Figure 11. Serious Injuries as a Function of LTV/Car Fleet Mix

The data predict a steady increase in AIS 3 and 4 injuries as LTV share increases. AIS 5 and 6 injuries also demonstrate a smaller but notable climb in injuries as LTV population grows. The general upward trend in all injuries with increasing LTVs in the fleet can be attributed largely to increased injuries in cars during LTV/car impacts, as well as injuries in single-vehicle LTV impacts. Although LTVs are generally assumed to provide greater self-protection than cars, field data shown in Figures 8 and 9 indicate that cars and LTVs demonstrate similar injury distributions in frontal impacts. This may be due to the fact that crash statistics also indicate that LTVs tend to be involved in single-vehicle



Baseline Car vs. Baseline LTV



Baseline Car vs. Reduced-Stiffness LTV

Figures 12 and 13. Crash Pulse Response in Baseline and Modified Car-LTV Crashes

crashes at slightly higher speeds. Because these results include all single- and two- vehicle collisions, cases resulting from single-vehicle and same-vehicle head-on impacts (car-car and LTV-LTV) simply scale up or down as a function of car or LTV population. Figure 11 demonstrates the net result of fleet mix changes within the accident environment, including aggressivity issues in LTV/car impacts as well as same-vehicle and different-vehicle impacts.

7.0 Future Aggressivity & Compatibility

The methodology can be applied to estimate harm in hypothetical future crash environments, to evaluate potential solutions to the current vehicle aggressivity and compatibility problem. In this approach, the vehicle models are specifically modified to reflect vehicle design changes aimed to reduce aggressivity. Such design changes may be in response to future regulations which may mandate compatibility among vehicles, or could be the result of independent redesign by automakers to address the LTV aggressivity problem.

In the previous section, the detailed statistical model of the environment was parametrically examined to evaluate injuries as a function of variations in fleet mix. Because the methodology also considers physical behavior in the accident environment (via computational modeling of vehicles and occupants), the effects of such design changes can be evaluated in terms of injuries across the entire frontal accident environment. This provides a useful tool for identifying the net effects and tradeoffs incurred when addressing the vehicle aggressivity problem, as opposed to single point simulation, where the broader context of a vehicle design change may be difficult to assess.

For this study, the LTV vehicle model was modified to reduce its overall stiffness by 15%. This was achieved by simply reducing the force-deflection behavior of all of the spring elements in the lumped-parameter LTV vehicle model. Such a reduction in stiffness may be achieved in a real

vehicle via a combination of structural modifications, such as material selection and stiffness, as well as part geometry. The LTV vehicle model was only modified to decrease its stiffness – its mass remained the same, and the Car model was left unchanged. Furthermore, the baseline comparison scenario, with unchanged vehicle stiffness, consists of 100% dual airbag availability. This is done on the basis that before a more “compatible” fleet (considered here as a less stiff representative LTV model) can be achieved, airbags will be completely phased into the future fleet.

Figures 12 and 13 illustrate the effectiveness of reducing the LTV’s stiffness in improving crash pulse behavior in both vehicles during a car/LTV head-on impact. Figure 12 shows the vehicles’ baseline acceleration in an impact with a closing speed of 116kph; clearly the car undergoes a far more severe deceleration than the LTV, peaking at 41G. In Figure 13, the car still undergoes a more severe crash pulse than the modified LTV, though not as severe as during the baseline crash case, peaking at less than 35G. The LTV crash response shows similar severity for the

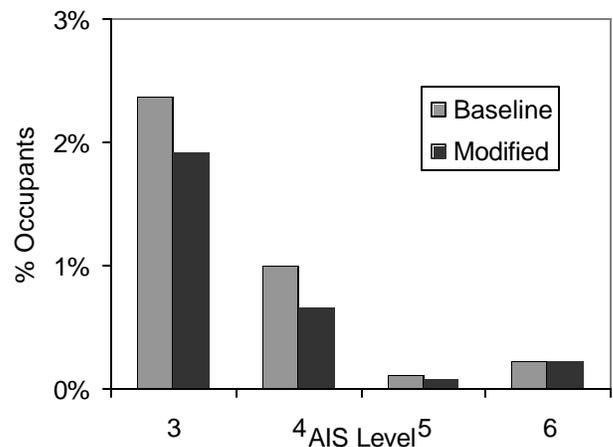


Figure 14. Reduction in Total AIS 3-6 Injuries due to Reduced-Stiffness LTV

Table 2. Annual Change in Injuries due to Reduced-Stiffness LTV Vehicle, Absolute Number of Occupants

AIS	TOTAL Environment	Single-vehicle impacts		Two-vehicle Head-on Impacts			
		Cars	LTVs	Car-Car	LTV-LTV	Car-LTV	LTV-Car
	n=427,260	n=252,091	n=89,742	n=42,922	n=9,318	n=18,940	n=14,248
0, 1, 2	3476	0	2421	0	415	736	-96
3	-1932	0	-1570	0	-265	-96	-1
4	-1446	0	-808	0	-132	-577	71
5	-98	0	-87	0	-4	-22	16
6	0	0	43	0	-13	-41	11

baseline and modified cases. Therefore, it is expected that injuries to car occupants in car-LTV crashes would generally decrease as a result of reducing LTV stiffness. To also consider other crashes, the net effect of this change within the entire frontal crash environment is demonstrated in Figure 14. While total fatalities are left unchanged by the modified LTV, AIS 3, 4, and 5 injuries show a noticeable decrease compared to the baseline scenario. Figure 14 illustrates the net environment effect of decreasing LTV stiffness, and therefore it is difficult to attribute the injury reduction to specific crash modes or vehicles. Table 2 provides a detailed breakdown of this data, in terms of net change in absolute number of injuries as a function of crash mode and vehicle type. The first column describes the entire frontal crash environment, as does Figure 14, in terms of absolute number of occupants. Note that the reduced-stiffness vehicle leads to the reduction of 3,476 annual AIS 3-5 injuries to the lesser AIS 0-2 categories. The second and fourth columns of Table 2 show a zero gain/loss in all injury categories, as the car model is unchanged for the two environments, leading to identical occupant harm results for single-vehicle car impacts and two-vehicle car-car impacts. The third column shows the results of single-vehicle LTV impacts: note that although the modified LTV model is less stiff than current LTVs, AIS 3-5 injuries are reduced substantially, with a concurrent increase of 43 fatalities. This suggests that reducing frontal stiffness in LTVs increases their self-protection in moderate severity single-vehicle impacts, though it may compromise LTV self-protection in very severe crashes, leading to the observed increase in single-vehicle LTV fatalities. In the right half of Table 2, injuries in two-vehicle crashes are described in terms of subject vehicle vs. partner vehicle. In LTV-LTV and Car-LTV collisions, AIS 3-6 injuries are reduced throughout, indicating that reducing the stiffness of LTVs always improves injury results in the partner vehicles, both cars and other LTVs. The rightmost column highlights the tradeoff incurred in LTV-car impacts: AIS 4-6 injuries increase within LTVs, including an increase of 11 fatalities. Therefore, while large safety gains can clearly be made when considering the entire frontal crash environment, smaller areas of reduced protection do exist and can be identified. Detailing the data as

shown in Table 2 provides a cross-sectional view of the various tradeoffs incurred when considering the aggressivity and compatibility problem.

The topic of vehicle aggressivity and compatibility is typically discussed in terms of three major vehicle parameters: mass, stiffness, geometry. While the study described here only addresses the stiffness issue and features relatively simple vehicle and occupant models, it serves as a useful tool for estimating injury reductions to be realized from a general reduction in LTV frontal stiffness.

8.0 Conclusions

A systems modeling methodology for estimation of harm has been presented and validated for a subset accident environment consisting of single- and two-vehicle frontal impacts. The model has been applied to study the sensitivity of total harm to fleet mix, wherein an incremental increase in LTV population is linked to a rise in moderate to severe injuries.

Components of the methodology include a statistical model providing a probabilistic description of the accident environment, vehicle models and occupant approximation functions for parametric simulation of crashes, and biomechanical transforms for estimation of injury in each case. The application model presented consists of 1,008 occupant cases, representing 384,000 drivers and passengers annually, 24,000 of which sustain a serious injury.

The model demonstrates that overall injury trends are very accurately estimated using the system modeling methodology described. The model predicts distribution of AIS level 3 through 6 injuries within 0.5% of all occupants for each AIS category in the entire subset environment. When validated against field data sorted by accident mode and vehicle type, the model demonstrates very close estimation of injuries, with greater percentage accuracy for cars occupants than for LTV occupants. For nearly all comparisons against field data the model slightly overestimates AIS 4 injuries while underestimating AIS 5 injuries by the same amount.

Observed differences between model results and field data indicate that there exist areas for potential improvement of the application model presented. The occupant approximating functions to estimate occupant injury from vehicle crash pulse may be refined to more accurately predict unrestrained conditions and possibly consider additional crash pulse characteristics as inputs. With regard to the vehicle models, all frontal collisions, including angled and offset frontal collisions, are simulated as full frontal impacts. Hence, some of the more severe injuries resulting from angled and offset impacts that occur in the field may not have been fairly represented by full frontal simulation. Injury compounding effects of combined injuries are not modeled, and injuries to body regions other than the head and chest are not considered. Further refinement of the statistical model to include more variable joint dependencies and greater resolution across continuous variables such as impact speed may lead to a more accurate prediction of overall harm. The vehicle models used could be improved by representing vehicle geometry, as the 1-dimensional models employed here are adequate for capturing vehicle mass and stiffness behavior, but do not consider geometric effects such as bumper height mismatch. Finally, the implemented biomechanical models, in terms of injury criteria and risk functions for estimating AIS levels from those criteria, are also subject to known limitations.

To study the problem of vehicle aggressivity and compatibility, LTV/car impacts were separately evaluated to identify serious injury trends within each subject vehicle. Car occupants were found to undergo significantly greater harm than their LTV counterparts, by a factor of 3:1 for AIS 3 and 4 injuries. While small numbers of AIS 5 and 6 injuries were predicted for car occupants, these injuries were nearly nonexistent for LTV occupants in LTV/car collisions. Also, the overall sensitivity of total occupant injuries as a function of LTV/car fleet mix was investigated. AIS 3 and 4 injuries were found peak with an LTV fleet share of 60%, while AIS 5 and 6 injuries were found to fall less steeply as cars became less prevalent. Furthermore, a study was conducted to evaluate changes in injury severity upon reducing LTV stiffness in a hypothetical future vehicle fleet. Results showed small absolute decreases in LTV self-protection in serious single-vehicle and LTV/car impacts, with large improvements in occupant protection in LTV partner vehicles in all 2-vehicle crashes.

Future work. This investigation is an ongoing effort to develop methods for evaluation of fleetwide aggressivity and compatibility in support of NHTSA research initiatives. Further studies will include 3-dimensional lumped parameter or hybrid vehicle models to capture occupant compartment response in angled and offset frontal impacts. The scope of the existing model will be expanded to include side impacts in addition to frontal impacts, and include sensitivity analyses to evaluate the relationship between vehicle crashworthiness in frontal collisions and aggressivity in side impacts. Long term developments include addition of optimization

capability to the methodology, to identify optimal vehicle features which lead to a minimization of overall harm.

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