A STOCHASTIC APPROACH FOR THE SIMULATION OF AN INTEGRATED VEHICLE AND OCCUPANT MODEL

Chin-Hsu Lin, Ruth Gao, Yi-Pen Cheng
General Motors, USA
Paper ID # 307

ABSTRACT

Stochastic simulation is used to account for the variation in the manufacturing and assembling processes of the vehicle structure and occupant restraint system. An integrated full vehicle model with belted driver, 50th percentile male Hybrid III dummy, subjected to a 35 mph zero degree impact test, is used to present the scatter in the vehicle crash and occupant restraint performance.

Yield stress of a typical mild steel has scatter values between 10 to 20% and a coefficient of variation of 5% is derived for scaling the stress and strain curve. The thickness tolerance has scatter values specified between 5 to 10% and a coefficient of variation of 2% is used in the study. The material properties and thickness of major structural components for absorbing impact energies, such as the motor/occupant compartment rails and upper rails, bumper beam, cradle, and toe pan are the random input variables for the structure. Characteristics of a restraint system also vary among the same design and a coefficient of variation of 5% is adopted in this study. The restraint system for the occupant, such as steering column stroke force, seat belt retractor force, airbag mass flow rate, and airbag deployment time, are the random variables selected in this study.

Typical injury criteria (head injury criteria (HIC), chest G, chest deflection, neck loads, and femur loads) and structural performance (intrusions of toe pan, steering column, and A-pillar) are extracted. These values are then used to determine the effect of the structural and the restraint system variations on the occupant and vehicle crash behaviors. The cross relationships between the structural crash behavior and occupant injury numbers are also studied.

INTRODUCTION

Current practices for validating vehicle programs, by either proving ground tests or math-based simulations, rely heavily on ideal deterministic conditions, even though it has been recognized that there are no identical test results from two so-called identical vehicles. The acceleration and velocity histories of two production vehicles subjected to 30mph zero degree rigid barrier frontal impact tests are shown in Figure 1 to demonstrate the differences in the pulses. The differences among the prototype vehicles and production vehicles are even more significant, since the prototype vehicles are genetically different from the production vehicles in the way that they are built and assembled. In practical design situations, the exact values of the random parameters may not be known and hence the effect on the outcome of the output variables can not be understood, unless a series of impact tests can be conducted. Math-based simulations would be a more desirable and economical method to perform the stochastic analysis and to understand the vehicle crash behaviors.

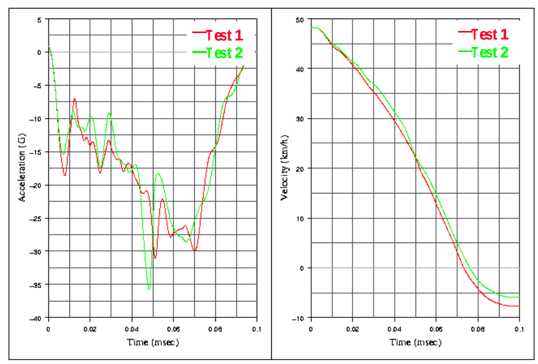

Figure 1. Acceleration and velocity pulses in the occupant compartment from 30mph zero degree rigid barrier frontal impact tests for two production vehicles.

PRELIMINARY STUDY OF THE STOCHASTIC ANALYSIS

To assess the mean and standard deviation of a vehicle design, Monte Carlo based stochastic vehicle analyses have been employed [1]. For achieving reliable results, the number of runs could be impractical, if the simple random sampling technique in iSIGHT [2] is employed, for dynamic nonlinear finite element simulation codes, such as LS-DYNA, PAM-CRASH, and RADIOSS. However, the other Descriptive Sampling technique available in iSIGHT is used as the sampling algorithm for the results presented in this paper. This Descriptive Sampling is an enhanced technique, which holds a distinct advantage over the simple random sampling method in particular by being more effective and having a faster rate of convergence over large design spaces. With this technique, the design space for each variable is divided into subsets of equal probability. All random variables are divided, before the actual simulations, into the same number of subsets. These spaces are then randomly combined (with fixed random seeds or non-fixed random seeds) to define the design matrix by selecting each subset of a variable only once. The number of sampling points can be reduced without sacrificing the quality of the statistical description.

For using the descriptive sampling technique, the number of runs needs to be predetermined so that the design matrix can be determined. To better understand the two sampling techniques and the number of runs necessary to achieve the desired accuracy of the mean and standard deviation, a cantilever beam problem is designed, shown in Figure 2, and Taylor's series is used to estimate the mean and its standard deviation. Deflection at the end of the cantilever beam is the function to be studied and it has the random variables of loading ***P***, beam length ***L*** and diameter ***D***, and Young's modulus ***E***.

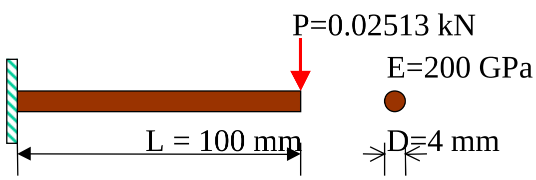

Figure 2. A cantilever beam.

To evaluate the mean and the variance of a function ***S***, we expand ***S*** by Taylor's series [3] with respect to small changes $\Delta\boldsymbol{x}$:

$$\boldsymbol{S}(\boldsymbol{x}) = \boldsymbol{s} + \frac{d\boldsymbol{S}}{d\boldsymbol{x}}\Delta\boldsymbol{x} + \frac{1}{2}\Delta\boldsymbol{x}^T\frac{d^2\boldsymbol{S}}{d\boldsymbol{x}^2}\Delta\boldsymbol{x} + \dots \quad (1).$$

In Equation 1, $\boldsymbol{S(x)}$ is the performance index of the parameters $\boldsymbol{x}=(x_1, x_2, ..)$, $\Delta\boldsymbol{x}^T$ is transpose of the $\Delta\boldsymbol{x}$, and $\boldsymbol{s}$ is the value of $\boldsymbol{S}$ evaluated at the mean values $\boldsymbol{x_0}$ and the derivatives are also evaluated at the mean values $\boldsymbol{x_0}$. Assuming all the design parameters have normal distribution, the mean of ***S*** can be obtained by taking the expectation on both sides of Equation 1 and dropping the higher order terms. The second term will be zero, when they are evaluated at $\boldsymbol{x_0}$, hence the mean can be estimated as

$$\hat{\boldsymbol{S}} \cong \boldsymbol{s} + \frac{1}{2}\sum_i \frac{d^2\boldsymbol{S}}{d\boldsymbol{x}_i^2}\sigma_i^2 \quad (2).$$

where $\hat{\boldsymbol{S}}$ is the mean value of ***S*** and σ_i^2 is the variance of design parameters. The variance can be estimated as

$$\boldsymbol{Var(S)} \cong \sum_i\left(\frac{d\boldsymbol{S}}{d\boldsymbol{x}_i}\right)^2\sigma_i^2 + \frac{1}{2}\sum_i\sum_j\left(\frac{d^2\boldsymbol{S}}{d\boldsymbol{x}_i d\boldsymbol{x}_j}\right)^2\sigma_i^2\sigma_j^2 \quad (3).$$

For the problem of a cantilever beam, the deflection ***S*** can be expressed:

$$S(P,L,E,D) = \frac{PL^3}{3E\frac{\pi}{4}\left(\frac{D}{2}\right)^4} \quad (4).$$

For the cantilever beam shown in Figure 2, if the coefficient of variation for each design parameter is 10% of the nominal value, then

$$\sigma_P^2 = (0.002513)^2; \sigma_L^2 = (10)^2; \quad \sigma_E^2 = (20)^2; \sigma_D^2 = (0.4)^2 \quad (5).$$

Hence, the mean can be estimated

$$\begin{aligned}\hat{\boldsymbol{S}} &= \boldsymbol{s} + \frac{1}{2}\frac{d^2\boldsymbol{S}}{d\boldsymbol{x}_i^2}\sigma_i^2 \\ &= 3.333 + (0 + 0.1 + 0.0333 + 0.333) \\ &= 3.333 + 0.466 = 3.799\end{aligned} \quad (6).$$

Using the Monte Carlo simulation simple random technique in iSIGHT, the mean converged to 3.793 after the convergent criteria set by iSIGHT were met with a total of 2,125 runs. The cloud of the beam diameter and its deflection is shown in Figure 3, note that the one-to-one perfect relationships disappear when all the design parameter variations are taken into account simultaneously in the simulations [4].

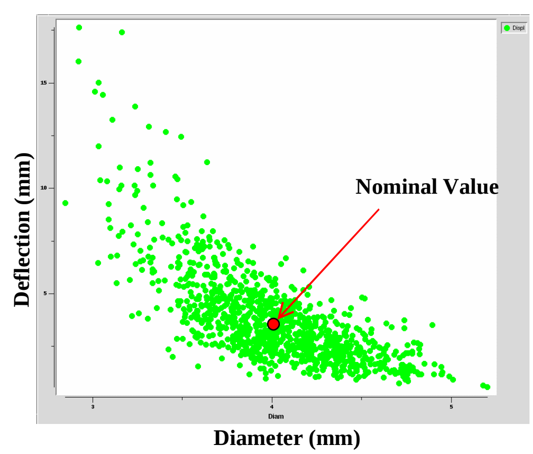

Figure 3. Plot from iSIGHT for the Monte Carlo simulation.

Assuming the design parameters are independent of each other, then one of the terms in Equation (3) can be eliminated

$$\frac{d^2 S}{dx_i dx_j} \sigma_{\boldsymbol{ij}}^{\boldsymbol{2}} = 0 \qquad (7).$$

Hence, the other terms in that equation can be evaluated as

$$\sum_i \left(\frac{d\boldsymbol{S}}{d\boldsymbol{x}_i} \right)^2 \sigma_{\boldsymbol{i}}^{\boldsymbol{2}} = 2.9994 \qquad (8).$$

$$\frac{1}{2} \sum_i \left(\frac{d^2 \boldsymbol{S}}{d\boldsymbol{x}_{\boldsymbol{i}}^{\boldsymbol{2}}} \right)^2 \left(\sigma_{\boldsymbol{i}}^{\boldsymbol{2}} \right)^2 = 0.2444 \qquad (9).$$

$$\frac{1}{2} \sum_i \sum_{j \neq i} \left(\frac{d^2 \boldsymbol{S}}{d\boldsymbol{x}_i dx_j} \right)^2 \sigma_{\boldsymbol{i}}^{\boldsymbol{2}} \sigma_{\boldsymbol{j}}^{\boldsymbol{2}} = 0.21662 \qquad (10).$$

Then

$$\boldsymbol{Var\ S} = 2.999 + 0.244 + 0.2166 = 3.460$$

After obtaining the variance of $\boldsymbol{S}$, the standard deviation, which is equal to 1.860, is calculated by taking the square root of the variance of $\boldsymbol{S}$. The estimated standard deviation from Taylor's series is different from the results from the Monte Carlo Simulation, which is equal to 2.206. The difference can be attributed to the fact that only lower order terms in the Taylor's series were included in this calculation.

If the coefficient of variation is set to be 2.5%, the Monte Carlo simulation in iSIGHT converged after 625 runs and it gave 3.358 for the mean and 0.4436 for its standard deviation. Taylor's series gives 3.362 for the mean and 0.435 for its standard deviation. These values are easily calculated by multiplying a factor from the results of 10% coefficient of variation. By reducing the coefficient of variation, the estimations from Taylor's series yield the results much closer to the Monte Carlo simulations. Results from Taylor's series and the iSIGHT simulations for one random variable at a time and all four random variables together were tabulated in Table 1.

In Table 2, we compare the results from different sampling techniques, ways of generating random seeds, and number of runs with 10% coefficient of variation. We can conclude from this study that results from the 50 runs with the descriptive sampling technique and fixed random seeds would give a good estimation of the mean and standard deviation.

BASELINE MODEL

The vehicle model is a non-linear finite element analysis model for LS-DYNA. The full vehicle model, shown in Figure 4, integrated the structure model with a belted driver and an airbag, and it has a total of 90K nodes. The frontal impact test configuration is a 35 mph zero degree rigid barrier test. To predict the occupant performance, the conventional practice is to extract structural deceleration characteristics and then apply the deceleration pulses to a system with a limited occupant compartment structure coupled with a dummy and restraint system. However, injury potential to the occupants in the case of a frontal impact is directly related to the decelerating vehicle coupled with the restraint system. Hence, a fully integrated vehicle model coupled with a finite element driver is employed for this study.

Figure 4. Integrate 50th percentile finite element dummy with vehicle structural model.

A robust and stable full vehicle model is a prerequisite for crash stochastic simulations. Simulations of the integrated vehicle on various computer platforms with a different number of CPUs and different versions of LS-DYNA executables were conducted. The simulation results were compared to each other to ensure that the vehicle system behaviors are consistent and dependable. In the end, the shape of the folded airbag was changed so that the sensitivity of the airbag deployment due to the contact algorithm in LS-DYNA was minimized. All the results presented in this paper were performed on an HP workstation using one CPU and LS-DYNA version 950d for operating system UX 10.2.

The experimental test has an HIC number of 658 and a chest G of 44 and the simulation gives the HIC number of 650 and chest G of 42.4, shown in Figure 5. Comparing the structural velocity pulses and occupant accelerations, one can conclude that the finite element analyses from this fully integrated vehicle model correlates well with the test. This baseline model took 92 CPU hours to complete the simulation with 0.6μs initial time step and 0.54μs ending time step.

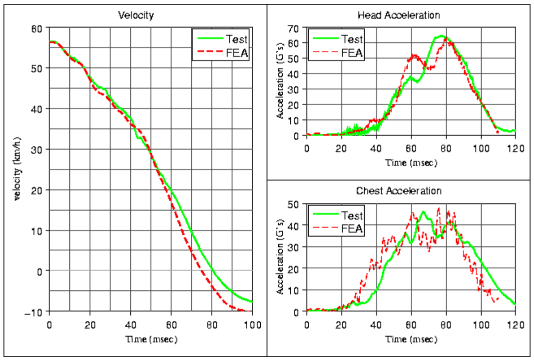

Figure 5. Results of the structural velocity pulse, head and chest accelerations from the proving ground test and finite element simulation.

VARIABLES OF THE STOCHASTIC ANALYSIS

There are numerous parts in the vehicle model, however, variation in some of the components may not contribute to the differences in the output variables under the frontal impact test conditions. In this study, the components selected were the major components, which could change the values of the output variables. For both structural components and the restraint system, a total of 18 critical design variables were selected as the random variables for the stochastic analysis.

The selected structural random variables were: mid-rail in motor compartment, mid-rail reinforcements, upper rails, cradle, bumper beam, mid-rail of the occupant compartment, and toe pan. The thickness has a coefficient of variation 2%, i.e., a standard deviation equal to 2% of the nominal value. While the material properties have a coefficient of variation 5%, the stress and strain curves of the materials were randomly scaled to reflect the variation of the material properties. Both of the component thickness and material properties are assumed to have a normal distribution for the probabilistic density function. The effect of the strain rate on the material behavior in a full vehicle crash is considered in this study. It has been demonstrated that it is important to consider the strain rate effect to account for higher yield stress and higher effective stress under the same content of effective strain [5].

The selected random variables of the restraint system were as follows: seatbelt retractor force, airbag mass flow rate, steering column stroke force, and airbag deployment time. Based on the engineering experience that the ranges of these variables are about +/- 10%, detailed characteristics of a restraint system are uncertain and a coefficient of variation of 5% was assumed. The probabilistic density functions of these variables are assumed to be normal distributions.

Fifty sampling points were generated from iSIGHT using the descriptive sampling method since the first two statistical values, mean and standard deviation, are the interest of this study and they converge quite quickly. In Figure 6, the sampling points of all the design spaces are projected onto the plane of mid-rail thickness and seatbelt retractor force variables to show the cloud of the sampling points. And the pre-defined normal distribution of the mid-rail thickness is confirmed in Figure 7, which is generated from Figure 6 by counting the number of occurrences in each subset.

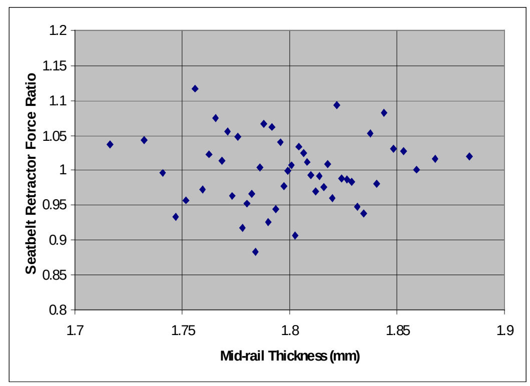

Figure 6. Scatter plot of two random variables mid-rail thickness and seatbelt retractor force ratio.

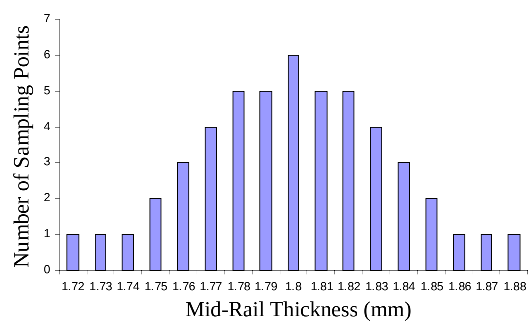

Figure 7. Histogram of the mid-rail thickness of the fifty data points.

Occupant injury numbers: Head Injury Criteria (HIC), chest G, neck load, chest deflection, and femur load were studied. The combined probability (CP) value [6] calculated from the head injury criteria (HIC) and chest G responses of the driver was also studied. For a vehicle performance to be rated as five-star under the New Car Assessment Program (NCAP), the CP values should be less than or equal to 10 percent; while a four-star rating is given for values greater than 10 percent but less than or equal to 20 percent. This study vehicle had an initial CP value of 0.125 for the nonlinear finite element simulation, which is classified as a four-star vehicle by NCAP.

For the structural performances, the intrusions of the toe pan, A-pillar, and steering column were studied. To reduce the sensitivity of the output variables from the nodal selection, the toe pan intrusion was an averaged intrusion of three nodes on the toe pan at the driver side. The A-pillar intrusion was an averaged intrusion of two nodes, picked from the A-pillar inner and outer panels at the driver side. As for the steering column intrusions, they were averaged from three adjacent nodes.

RESULTS OF THE STOCHASTIC ANALYSIS

Fifty LS-DYNA input decks were generated and then the decks were manually submitted to available computers. All fifty runs were completed. Forty-four of them were completed without any modifications of the input decks. The remaining six runs required minor modifications (added an extra contact surface, increased the number of integration points on the shell plane for two parts, and split two quadratic elements into triangular elements) in order to complete the simulations without having the model become unstable.

A few selected cloud plots from the 50 runs are shown in Figures 8 through 11. In Figure 8, the cloud of the stochastic finite element simulations is shown on the star rating contour. It shows that most of the simulations fall within the 4-star range, while 4 simulations out of the 50 are in the 5-star range. It needs to be pointed out that the material properties and thicknesses were assumed uniformly changed for an entire component in our simulation, while the actual differences may only fluctuate from location to location. Hence, the results reported in this study tend be more conservative, i.e., larger standard deviation or more widely spread points.

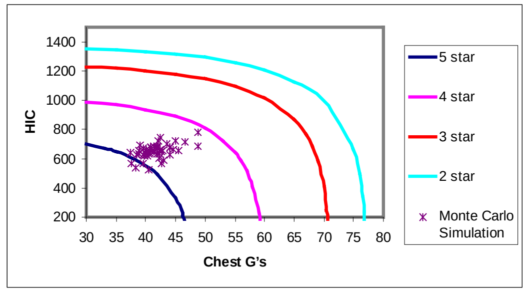

Figure 8. Scatter plot of the stochastic analysis results on the plane of output variables HIC and chest G.

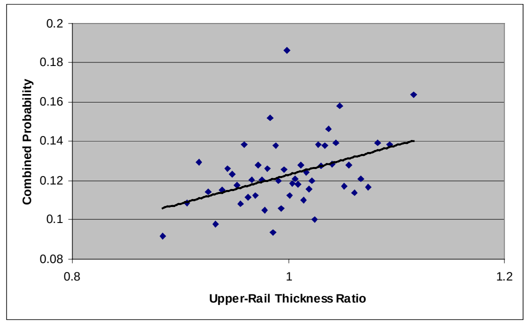

Figure 9. Cloud plot of the upper rail thickness ratio versus the CP.

Figure 9 shows the cloud plot of the upper rail thickness ratio versus the CP. A regression curve fit was drawn using a power fit function in Microsoft Excel to show the trend of the random variables versus the CP. The regression curve has the form of $y=ax^c$, where x and y are the variables and a and c are the coefficient and the order of the variable x respectively. From the line in Figure 9 drawn by the regression analysis, one can conclude that the change of the upper rail thickness has a direct effect on the CP, i.e., the increase of the upper rail thickness tends to increase the CP. The trend from the regression curve can be confirmed by the linear Pearson's correlation coefficient r=0.423, which is calculated from the formula

$$r = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (y_i - \bar{y})^2}} \qquad (11).$$

where $\bar{x}$ and $\bar{y}$ are the means of the x_i's and y_i's respectively. Measure r is a dimensionless index that ranges from -1.0 to +1.0 and reflects the extent of a linear relationship between two data sets. A +1.0 indicating that the two data sets are directly related and in perfect agreement, i.e., the data points lie on a perfect straight line with the two variables increasing together [7]. A –1.0 indicates that the two data set are inversely related but in perfect agreement. A near zero *r* indicates that the two variables are uncorrelated.

The effects of the input design variables on the structural and occupant performances are listed in Table 3. A summary of the input variables effects on the output variables and its correlation coefficients are compiled in Table 4. For the case of the upper rail thickness among other structural random variables, *r* is equal to 0.423, which has the most direct effect on outcome of the CP, i.e., increasing in upper rail thickness tends to increase the CP. While for the restraint system, the steering column stroke force has the most direct effect on the CP. From the cloud of the seat belt retractor force versus the CP (shown in Figure 10) and the Pearson's correlation coefficient ($r = -0.454$), one can conclude that the seat belt retractor force has the most reverse effect on the CP. While the other random variables, e.g., cradle thickness, airbag mass flow rate, and airbag deployment time (shown in Figure 11) did not correlate with the output variable CP within the ranges studied. A phenomenon observed from the regression analysis is that the behaviors between the input and output variables are linear.

To improve the performance of the CP, one would reduce the upper rail thickness and nominal values of other variables, which have direct effect on the CP, and increase the seat belt retractor force and nominal values of the other variables, which have the reverse effect on the CP. All the input random variables are assumed having the normal probabilistic distribution and the output variable CP shows a very similar normal distribution, shown in Figure 12, with the mean of 0.124 and the standard deviation of 0.018. One of the extreme data, which has its CP equal to 0.19, may be the result from the numerical simulation itself rather than from the actual crash behavior. The normal distribution of the CP itself indicates that the system design is quite stable and no existence of chaotic behaviors.

There is more structural intrusion from the 40mph offset deformable barrier (ODB) impact test then the NCAP impact test. And it is a common practice to enhance the system for ODB impact test by reducing the amount of intrusion, while for the NCAP impact test, the velocity pulse of the structure would be softened to decrease the deceleration pulse and hence improve the occupant performances. However, the amount of the intrusions from the toe pan and A-pillar in the NCAP impact test could affect the steering column motion, which would then have direct effects on HIC and Chest G. The cross relationships between the structural behaviors and the occupant performances are summarized in Table 5. The femur loads shown in the table are very sensitive (larger correlation coefficients) to the knee-height, which are directly affected by the amount of intrusion from toe pan and knee bolster. Clouds of the intrusions versus the femur loads are shown in Figures 13 and 14.

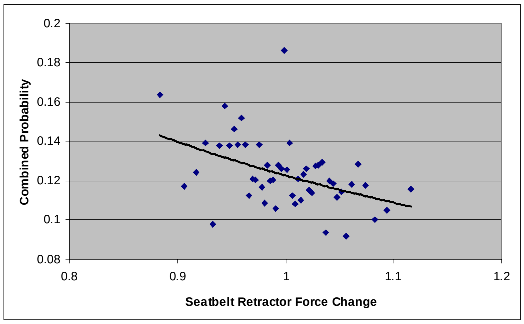

Figure 10. Cloud plot of the seat belt retractor force versus the CP.

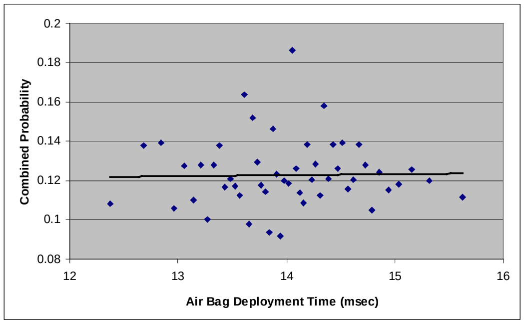

Figure 11. Cloud plot of the air bag deployment time versus the CP.

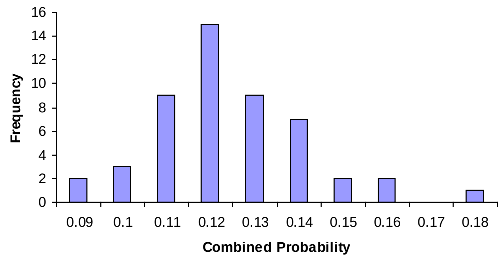

Figure 12. Combined probability histogram.

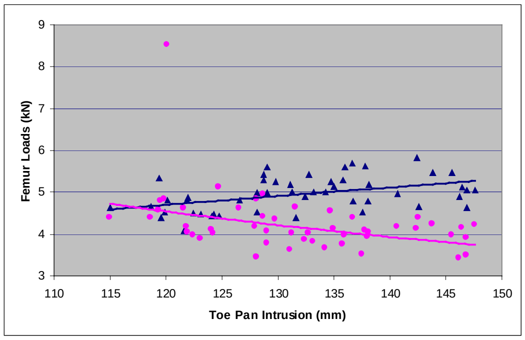

Figure 13. Cloud of toe pan intrusion versus femur loads (blue triangles for the left leg and pink dots for the right leg).

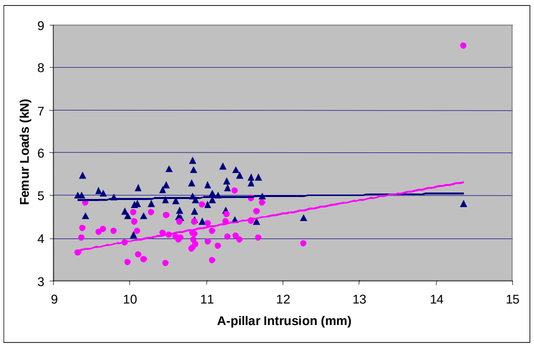

Figure 14. Cloud of A-pillar intrusion versus femur loads (blue triangles for the left leg and pink dots for the right leg).

CONCLUSIONS

A stochastic approach for the simulation of an integrated vehicle and occupant model was developed. The Monte Carlo sampling techniques in iSIGHT were compared with the estimations from lower order Taylor's series. The thickness and material properties of the major components for the frontal impact tests and major design variables for the occupant restraint system were studied. From the stochastic analysis results, it could be seen that instead of a deterministic solution, clouds of the design variables versus performance variables were plotted and examined.

The effects of the upper rail thickness, steering column force, and seat belt retractor force dominate the performance of the CP. To reduce the CP and improve the system performance, it appears that the upper rail thickness and the steering column force should be reduced along with an increase of the seat belt retractor force. Having normal probabilistic distribution for all the design variables, the CP variable has a similar normal distribution as well. The factors which dominate the effect on the system performances could be varied using the Monte Carlo technique to search for a robust and reliable design, which is a subject being studied.

ACKNOWLEDGEMENTS

The authors are deeply indebted to the GM Crash and Safety Focus Group for their support. The helpful discussions from Yih-Charng Deng and Ching-Chieh Hsieh are greatly appreciated.

REFERENCES

1. Joseph Hassan, Guy Nusholts, and Marlon D. Forrest, *A Stochastic Approach for Occupant Crash Simulation*, SAE 200-01-1597, 2000 Future Car Congress Arlington, Virgin, April 2-6, 2000.
2. iSIGHT v5.0, Engineous Software, Inc.
3. C-C Hsieh, K P Oh, *MARS: A Computer-Based Method For Achieving Robust System*, FISITA 92 conference, 7-11 June 1992, London, The Integration of Design and Manufacture, Vol. 1, pp. 115-120.
4. J. Marczyk (Ed.), *Principles of Simulation-Based Computer-Aided Engineering*, Artes Graficas Torres, September 1999.
5. Kumar Mahadevan, Paul Liang, and Jim Fekete, *Effect of Strain Rate in Full Vehicle Frontal Crash Analysis*, SAE Technical Paper Series 2000-01-0625, March 6-9, 2000.
6. James R. Kackney, and Charles J. Kahane, *The New Car Assessment Program: Five Star Rating System and Vehicle Safety Performance Characteristics*, SAE Technical Paper Series 950888, February 27-March 2, 1995.
7. W. Press, S. Teukolsky, W. Vetterling, and B. Flannery, *Numerical Recipes-The Art of Scientific Computing*, Cambridge University Press, 1992.

Table 1. Comparison of the means and their standard deviations obtained from simulation and Taylor's series for both 10% and 2.5% of the coefficients of variation

Design Variable	***Coefficient of Variation 10%***				***Coefficient of Variation 2.5%***			
	Taylor Series		**iSIGHT**		**Taylor Series**		**iSIGHT**	
	Mean	Std Dev	Mean	Std Dev	Mean	Std. Dev	Mean	Std Dev
P	3.333	0.333	3.327	0.342	3.333	0.083	3.329	0.084
L	3.433	1.010	3.428	1.049	3.339	0.250	3.334	0.256
E	3.366	0.337	3.379	0.356	3.335	0.083	3.342	0.086
D	3.666	1.414	3.730	1.696	3.354	0.335	3.356	0.347
P, L, E, D	3.799	1.860	3.793	2.206	3.362	0.435	3.358	0.444

Table 2. Comparison of the means and their standard deviations from different sampling techniques, ways of generating random seeds, and the number of runs. The coefficient of variation was equal to 10%. The numbers in red and bold were the means, which are within +/- 0.1 (i.e., 3.693~3.893) of the converged value 3.793 and the standard deviations, which are within +/- 0.2 (i.e., 2.006~2.406) of the converged value 2.206.

Runs	**Monte Carlo - Simple Random**				**Monte Carlo - Descriptive Sampling**			
	Fixed Random Seeds		Non-Fixed Random Seeds		Fixed Random Seeds		Non-Fixed Random Seeds	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
100	3.830	2.138	3.830	2.138	3.867	2.255	3.867	2.255
	3.830	2.138	3.805	2.120	3.867	2.255	3.850	2.187
	3.830	2.138	3.826	2.396	3.867	2.255	3.883	2.328
50	**3.503**	2.220	**4.157**	2.022	3.866	2.252	3.866	2.252
	3.503	2.220	3.954	**2.543**	3.866	2.252	3.945	**2.915**
	3.503	2.220	**3.657**	**1.602**	3.866	2.252	3.816	2.219

Table 3. The correlation coefficients, in red if the absolute value is larger than 0.4, of the input and output variables

	A-pillar Intru.	Toe Pan Intru.	Steering Column Vertical Intru.	Steering Column Horizontal Intru.
Toe Pan Th.	0.175	0.003	0.068	0.006
Mid-rail Th.	-0.065	-0.086	-0.147	0.100
Bumper Beam Mat.	0.218	0.015	0.017	-0.128
Upper Rail Th.	0.136	**-0.452**	0.190	**-0.444**
Bumper Beam Th.	-0.342	0.001	-0.267	0.283
Cradle Th.	-0.004	-0.200	0.250	-0.333
Mid-rail Reinforce. Th.	0.033	-0.163	-0.086	-0.151
Mid-rail Mat.	0.030	-0.118	-0.026	-0.058
Occup. Comp. Rail Th.	0.289	**-0.789**	**0.527**	**-0.477**
Toe Pan Mat.	0.024	-0.102	-0.064	0.058
Upper Rail Mat.	0.199	-0.202	0.009	-0.162
Mid-rail Reinforce. Mat.	0.151	0.011	-0.018	0.075
Cradle Mat.	-0.054	0.001	-0.029	-0.073
Occup. Comp. Rail Mat.	0.205	**-0.504**	**0.471**	**-0.415**

	HIC	Chest G	Chest Deflect.	L. Femur Load	R. Femur Load	Neck Ten. Flex.	Neck Comp. Ext.	Neck Ten. Ext.	Neck Comp. Flex.	CP
Toe Pan Thick.	-0.051	-0.215	0.053	0.064	-0.007	0.075	-0.232	-0.207	0.051	-0.152
Mid-rail Th.	0.158	0.095	0.351	0.009	-0.180	0.191	0.138	0.258	0.138	0.114
Bumper Beam Mat.	0.148	0.168	0.255	0.102	0.038	0.100	0.075	0.032	0.061	0.172
Upper Rail Th.	0.212	**0.535**	-0.180	-0.103	0.329	-0.173	-0.030	-0.123	-0.150	**0.423**
Bumper Beam Th.	-0.206	-0.053	0.071	0.165	-0.189	-0.005	-0.204	-0.198	0.008	-0.120
Cradle Th.	0.028	-0.047	-0.008	-0.075	0.185	-0.028	-0.119	-0.030	-0.038	-0.049
Mid-rail Reinforce. Th.	0.027	0.197	-0.045	0.134	0.217	0.025	0.056	0.077	0.028	0.133
Mid-rail Mat.	0.186	0.046	0.034	0.017	0.030	0.081	-0.127	-0.115	0.072	0.100
Occup. Comp. Rail Th.	0.159	0.083	**0.427**	-0.257	0.222	0.050	-0.060	0.064	0.038	0.118
Toe Pan Mat.	0.231	0.242	-0.065	0.381	-0.176	-0.140	0.006	0.037	-0.140	0.272
Upper Rail Mat.	0.266	0.318	0.202	0.126	0.184	0.055	-0.099	-0.124	0.030	0.329
Mid-rail Reinforce. Mat.	0.066	0.241	0.162	0.064	0.003	0.131	0.245	0.176	0.118	0.167
Cradle Mat.	-0.300	-0.083	-0.089	-0.042	0.375	-0.074	0.000	0.048	-0.091	-0.224
Occup. Comp. Rail Mat.	0.179	0.082	-0.125	**-0.442**	0.278	-0.273	-0.160	-0.094	-0.287	0.133
Air Bag Mass Flow Rate	-0.120	0.077	0.148	-0.159	-0.187	**-0.418**	-0.118	-0.067	**-0.433**	-0.004
Steering Col. Force	**0.583**	0.231	**0.520**	-0.100	-0.096	**0.573**	0.141	0.244	**0.567**	**0.425**
Air Bag Deploy. Time	0.113	-0.067	0.068	0.037	-0.066	0.014	0.114	0.127	-0.108	0.004
Seat Belt Retractor Force	-0.254	**-0.517**	0.040	0.048	-0.100	0.111	0.088	0.223	0.074	**-0.454**

Table 4. Summary of the random variables effect on the outcome of the CP and their Pearson's correlation coefficients in parenthesis.

	Reverse Effect	Direct Effect	No Significant Effect
Thickness	• Toe pan (-0.152)* • Bumper beam (-0.120)	• Upper rail (0.423) • Mid-rail reinforcement (0.133) • Occupant compartment rail (0.118) • Mid-rail (0.114)	• Cradle (-0.049)
Material Property	• Cradle (-0.224)	• Upper rail (0.329) • Toe pan (0.272) • Bumper beam (0.172) • Mid-rail reinforcement (0.167) • Occupant compartment rail (0.133) • Mid-rail (0.100)	
Restraint System	• Seatbelt retractor force (-0.454)	• Steering column stroke force (0.425)	• Airbag mass flow rate (-0.004) • Airbag deployment time (0.004)

Table 5. The correlation coefficient, in red if the absolute value is larger than 0.4, between the structural performance and occupant performance

	HIC	Chest G	Chest Deflect.	L. Femur Load	R. Femur Load	Neck Ten. Flex.	Neck Comp. Ext.	Neck Ten. Ext.	Neck Comp. Flex.	CP
Toe Pan Intru.	-0.299	-0.266	-0.160	**0.438**	-0.389	0.190	0.191	0.124	0.180	-0.297
A-pillar Intru.	0.310	0.167	0.205	0.067	**0.551**	-0.108	-0.149	-0.116	-0.109	0.260
Steering Column Vertical Intru.	0.165	0.049	0.056	**-0.488**	**0.444**	-0.307	-0.127	-0.078	-0.268	0.116
Steering Column Horizontal Intru.	-0.230	-0.197	-0.008	0.380	**-0.631**	0.266	0.124	0.083	0.261	-0.240