Optimization and robustness for crashworthiness of side impact

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Abstract: This paper presents a nonlinear response surface-based safety optimisation and robustness process. The stepwise regression and optimal Latin hyper cube sampling methods are employed to construct the 'efficient-to-compute' surrogate model. A sequential quadratic programming method with mixed type of variables is employed for the design optimisation. A reliability based design optimisation model for robust system parameter design of vehicle safety is proposed and a Monte Carlo based stochastic simulation is used to perform the robustness assessment and the reliability-driven robust design. The methodology has been applied to the vehicle crash safety design of side impact. It shows that the vehicle weight can be significantly reduced with an improved safety performance and with a higher level of confidence. CAE simulation is used to validate the optimal results.

Keywords: crashworthiness, Monte Carlo method, optimal Latin hyper cube, optimisation, response surface method, robust design, stepwise regression, vehicle safety.

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1 Introduction

Computer analysis of crashworthiness has become a powerful and efficient tool. It can substantially reduce the cost and time required for the development and certification of new vehicle designs. Over the past ten years, tremendous increases in computer power and rapid evolution and development of theoretically sound, robust and efficient technologies for the simulation of nonlinear structural dynamics have advanced vehicle crash simulation to the point where the results are trusted with a high degree of confidence.

The resulting surge in technologies and computers is revolutionising the way vehicles are designed. However, the optimum and robust design for crashworthiness has rarely been found in the literature. Yang *et al.* (1994) published a feasibility study of vehicle safety CAE optimisation. Schramm and Thomas (1998) developed a global approximation method for structural crashworthiness design. Choi and Cho (1998) derived an analytical sensitivity method for an impact load. Blumhardt (1999) used different optimisation strategies for vehicle crash optimisation. Yu and Yajima (2000) developed a statistical design support system for the design of the reinforced members and the vehicle safety equipment. Based on the optimal Latin hyper cube sampling (LHS), Sudjianto (1998) *et al.* demonstrated an efficient computational procedure to emulate a computationally intensive complex CAE model by using multivariate adaptive regression splines (MARS). Sobieski *et al.* (2000) optimised a car body with NVH and roof crush constraints, using a 256-cpu SGI Origin 2000 computer. Chargin and Miura (1999) used response surface method to optimise crashwortiniess problems. Stander

(1999) investigated the similar problems using both response surface methodology and massively parallel programming. Yang *et al.* (2000) studied the best approximation methods for safety optimisation of large systems.

This paper presents an application of the approximation methods to the vehicle design for side impact. A nonlinear response surface based, deterministic optimisation is first presented to obtain a more balanced and cost effective design. The main goal is to further enhance side impact crash performance while minimising vehicle weight. All the responses are computed by using explicit nonlinear finite element software RADIOSS (1998). The optimal LHS is used to select the sample design points and the stepwise regression method is used to construct the response surfaces. Numerical optimization is carried out by using a sequential quadratic programming (SQP) method with mixed type of design variables.

One key component in this research is the robustness assessment and robust design using a reliability based design optimization (RBDO) model. In many vehicle safety optimization applications, the uncertainty of the quantities is only considered by using safety factors. In the study, the robustness assessment and robust design is obtained by modelling the variables with uncertainties. The uncertainties are resulting from many sources, e.g., engineering simulation, manufacturing process, etc. A statistical description of the random variables is necessary. Robustness assessment is performed by constructing an empirical cumulative distribution function (CDF) of the response variable generated from Monte Carlo simulation. In the RBDO model for the robust system parameter design, mean values of random variables are used as design variables and the vehicle weight is optimised subject to prescribed probabilistic constraints. The solution provides not only an improved design but also a specified level of confidence in the design. Numerical results are given and discussed for the benchmark vehicle side impact model.

2 Model and design targets

A typical vehicle side impact model is shown in Figure 1. With a finite element dummy model, the total number of elements in this model is about 90 000 and total number of nodes is around 96 000. The initial lateral velocity of the side deformable barrier is 31 mph. The CPU time for a RADIOSS simulation of the model is about 20 hours on a SGI Origin 2000.

For side impact protection, the vehicle design must meet internal and regulated side impact requirements specific to the vehicle market. The two primary side impact protection modes are the National Highway Traffic Safety Administration (NHTSA) side impact procedure (North American Vehicles FMVSS/CMVSS) or the European Enhanced Vehicle-Safety Committee (EEVC) side impact procedure (European Vehicles). In our study, EEVC side impact test configuration was used. The dummy performance is the main metric in side impact, which includes head injury criterion (HIC), abdomen load, pubic symphysis force, V*C's (viscous criterion) and rib deflections (upper, middle and lower). These dummy responses must at least meet EEVC requirements. A finite element dummy model was employed for prediction. Other concerns in side impact design are the velocity of B-Pillar at the middle point and velocity of the front door at the B-Pillar.

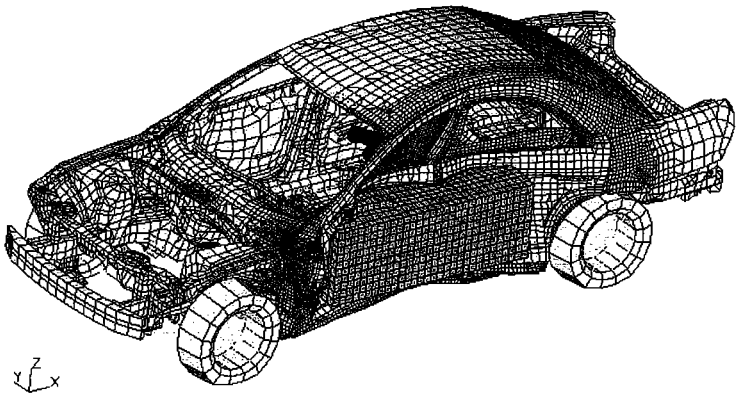


Figure 1 Side impact model.

For side impact, the increase of gauge design variables may in some cases improve dummy performance. However, it also increases vehicle weight, which is undesirable for fuel economy. Therefore, a balance must be sought between weight reduction and safety performance. The optimization problem in this research is to maintain or improve dummy safety performance, in this case measured by the EEVC side impact safety rating score, while reducing weight. The safety rating score consists of four measurements of the dummy: HIC, abdomen load, rib deflection or V*C, and pubic symphysis force. The highest score for each of these regions is 4 points and employs a sliding scale. A maximum of 16 points may be obtained for the vehicle side impact. Table 1 lists all the design targets for the benchmark model along with the EEVC regulation and the top safety rating criteria for vehicle side impact.

Table 1 Regulations and requirements for side impact.

Performance		EEVC Regulation	Top safety rating criteria	Baseline value	Design constraints
Abdomen load (kN)		2.5	≤ 1.0	0.663	≤ 1.0
Rib deflection (mm)	upper	42	≤ 22	28.5	≤ 32
	middle	42	≤ 22	29.0	≤ 32
	low	42	≤ 22	34.0	≤ 32
*V*C* (m/s)	upper	1.0	≤ 0.32	0.22	≤ 0.32
	middle	1.0	≤ 0.32	0.21	≤ 0.32
	low	1.0	≤ 0.32	0.31	≤ 0.32
Pubic symphysis force (kN)		6	≤ 3.0	4.067	≤ 4.0
HIC		1000	≤ 650	229.4	≤ 650

The optimization problem for side impact can be described as:

Minimise Weight

Subject to Abdomen load $\leq$ 1.0 kN

$V^*C \leq 0.32$ m/s

D_{urd} (upper rib deflection) $\leq$ 32 mm

D_{mrd} (middle rib deflection) $\leq$ 32 mm

D_{lrd} (lower rib deflection) $\leq$ 32 mm

F (Pubic symphysis force) $\leq$ 4.0 kN

$V_{B\text{-}Pillar}$ (Velocity of B-pillar at middle point) $\leq$ 9.9 mm/ms

$V_{front\ door}$ (Velocity of front door at B-pillar) $\leq$ 15.70 mm/ms

There are 11 design variables used for side impact optimization. The control variables are thicknesses and materials of critical parts, as shown in Table 2. All the thickness design variables are continuous, which are allowed to be varied over the range from $0.5 \times t_0$ to $1.5 \times t_0$, where t_0 is the baseline value. All the material design variables are discrete, which can only be either mild steel or high strength steel. The noise factors are barrier height and hitting position which are continuous and vary from –30 mm to 30 mm according to the physical test. The noise factors are used only in the robustness assessment and robust system parameter design.

Table 2 Design and noisy factors.

Design and noisy variable	Side constraints	Baseline value	No. of levels
Thickness of B-pillar inner	$0.5\,x_1^0 \leq x_1 \leq 1.5\,x_1^0$	x_1^0	10
Thickness of B-pillar reinforcement	$0.5\,x_2^0 \leq x_2 \leq 1.5\,x_2^0$	x_2^0	10
Thickness of floor side inner	$0.5\,x_3^0 \leq x_3 \leq 1.5\,x_3^0$	x_3^0	10
Thickness of cross members	$0.5\,x_4^0 \leq x_4 \leq 1.5\,x_4^0$	x_4^0	10
Thickness of door beam	$0.5\,x_5^0 \leq x_5 \leq 1.5\,x_5^0$	x_5^0	10
Thickness of door belt line reinforcement	$0.5\,x_6^0 \leq x_6 \leq 1.5\,x_6^0$	x_6^0	10
Thickness of roof rail	$0.5\,x_7^0 \leq x_7 \leq 1.5\,x_7^0$	x_7^0	10
Material of B-pillar inner	x_8: MS or HSS	MS	2
Material of floor side inner	x_9: MS or HSS	MS	2
Barrier height	$30 \leq x_{10} \leq 30$	0	10
Barrier hitting position	$30 \leq x_{11} \leq 30$	0	10

MS: Mild steel

HSS: High strength steel

2.1 Response Surface Method (RSM)

The response surface methods have been widely used in the design optimization and robust design (Mavris and Bandte, 1997). The main reason for its popularity is its easy application to numerous computer simulation problems. Another benefit for using the RSM is that the main effect of the responses can be determined explicitly.

In this research, the RSM is employed to develop a 'model-free' nonlinear model based on a set of multivariate data. An optimal Latin hyper cube sampling (LHS) and a quadratic stepwise regression (SR) methods are used to build response surfaces. The SR has been described as the best of the variable selection procedures and was highly recommended by Draper and Smith (1966). It was also found to be very accurate and robust for the approximation of safety related performance (Yang, *et al.*, 2000).

The optimal LHS (Currin *et al.*, 1991) was used to generate a sample of design points for the construction of the SR response surface. The optimal LHS was selected due to the absence of *a priori* knowledge of the parametric form of the model. Therefore, the experimental design is directed to minimise the bias part of the mean square error by distributing the sample points uniformly over the entire design region. The number of CAE simulations in the optimal LHS is determined by the total number of factors including control variables and noise variables. The minimum number of simulations is $3N$, where N is the total number of design variables. The number of levels for each variable can be very flexible. In the benchmark problem, the number of levels for all of the thicknesses (x_1 through x_7) and noise factors (x_{10} and x_{11}) was selected to be 10, while all the materials (x_8 and x_9) had 2 levels. A total of 33 runs analyses were performed.

There are many computational methods available for performing multiple stepwise regression calculations (Draper and Smith, 1966). The SR model used in this study is built by combining the techniques of forward selection with backward elimination (Yang *et al.*, 2000).

For the side impact finite element model, the SR response surfaces for the objective and constraint functions obtained from $3N$ optimal LHS were summarised as follows:

$$\text{Weight} = 2 + 4.9x_1 + 6.7x_2 + 7x_3 + 4x_4 + 1.8x_5 + 2.7x_7 \tag{1}$$

$$V_{\text{B_pillar}} = 10.6 - 0.67x_1x_2 - 2.0x_2x_8 + 0.02x_3x_{10} - 0.02x_4x_{10} + 0.28x_6x_{10} \tag{2}$$

$$V_{\text{Door}} = 16.4 - 0.49x_3x_4 - 0.84x_5x_6 + 0.43x_9x_{10} - 0.56x_9x_{11} + 0.0.0008x_{11}x_{11} \tag{3}$$

$$F_{\text{Abdomen load}} = 1.163 - 0.3717x_{10}x_2 - 0.484x_3x_9 + 0.01343x_6x_{10} \tag{4}$$

$$V^* C_{\text{up}} = 0.28 - 0.016x_1x_2 - 0.19x_2x_7 + 0.014x_3x_5 + 0.01x_5x_{10} + 0.08x_6x_9 + 0.001x_8x_{11} \tag{5}$$

$$V^* C_{\text{low}} = 0.74 - 0.61x_2 - 0.13x_3x_8 + 0.0012x_3x_{10} - 0.17x_7x_9 + 0.023x_2x_2 \tag{6}$$

$$\text{Deflection}_{\text{up}} = 29 - 4.2x_1x_2 - 7.8x_7x_8 + 0.021x_5x_{10} + 6.6x_6x_9 + 0.32x_9x_{10} \tag{7}$$

$$\text{Deflection}_{\text{low}} = 46.4 - 9.9x_2 - 12.89x_1x_8 + 0.11x_3x_{10} \tag{8}$$

$$F_{\text{Pubic force}} = 4.7 - 0.5x_4 - 0.19x_2x_3 - 0.012x_4x_{10} + 0.009x_6x_{10} + 0.0002x_{11}x_{11} \tag{9}$$

In the above stepwise regression formulations, the weight was assumed to be a linear function of the variables while all the other responses were assumed to be a quadratic function.

3 Optimization and robustness assessment

Based on the SR surrogate models, the optimization process is performed using the sequential quadratic programming (SQP) with mixed type of variables. A Monte Carlo simulation has been conducted for the robustness assessment. The advantage of using the SR surrogate models is a significantly reduced execution time, allowing a Monte Carlo simulation to be applied to the surrogate models rather on the actual finite element model. The flowchart of the procedure is displayed in Figure 2.

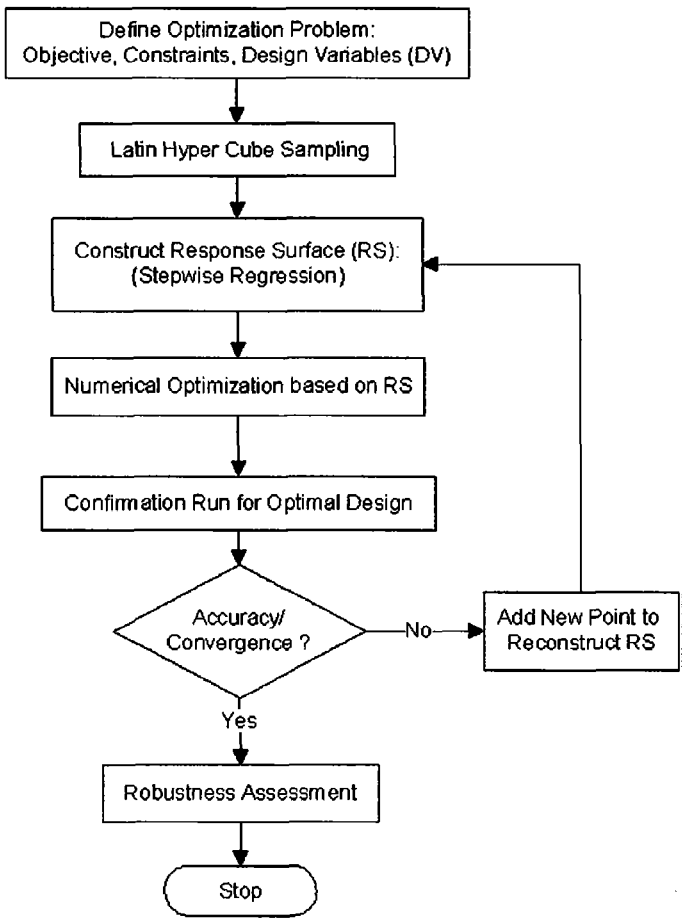


Figure 2 Optimization and robustness assessment process.

Three iterations were performed for the benchmark problem. In each iteration, the optimum design results are compared with the re-analysis solution. If the re-analysis solution is not satisfied, new SR models are rebuilt up by adding the re-analysis results and the optimization process is continued using the new response surfaces. It takes about 10 minutes on a HP workstation for one optimization iteration. The total number of CAE simulations was 37. Optimization and reanalysis results of three iterations are summarised in Table 3. The weight shown in Table 3 was calculated only from those

parts in which the gauges are defined as design variables. The vehicle safety performance is measured by its safety rating score. For side impact, a maximum of four points is assigned to each of chest, abdomen, pelvis and head regions. Table 4 summarises the safety rating scores for both baseline design and the optimal designs. The safety rating scores are calculated from the third optimization iteration.

Table 3 Results of optimum design.

	Baseline	1st Iteration		2nd Iteration		3rd Iteration	
		Prediction	Confirm-ation	Prediction	Confirm-ation	Prediction	Confirm-ation
Weight (kg)	29.18	25.79	25.62	23.52	23.59	23.56	23.59
Abdomen load (kN)	0.66	0.30	0.46	0.59	0.51	0.57	0.55
D_{up} (mm)	28.53	25.97	27.34	28.67	28.27	29.38	30.98
D_{mid}(mm)	28.99	29.73	26.39	29.21	27.46	27.66	27.49
D_{low} (mm)	33.95	32.00	29.97	32.00	31.57	32.00	30.98
V^*C_{lup}m/s	0.22	0.22	0.22	0.23	0.24	0.23	0.25
V^*C_{lmid}m/s	0.21	0.18	0.20	0.21	0.20	0.20	0.21
V^*C_{low}m/s	0.31	0.28	0.26	0.27	0.29	0.29	0.27
FPS(kN)	4.07	4.00	3.89	4.00	4.01	4.00	4.0
$V_{B\text{-}Pillar}$ (mm/ms)	9.9	9.72	9.07	9.33	9.36	9.34	9.53
$V_{front\ door}$ (mm/ms)	15.69	15.69	15.87	15.69	15.78	1569	15.75

Table 4 Safety rating score.

	Baseline design		Optimum	
	Results	Score	Results	Score
Abdomen force (kN)	0.663	4	0.55	4
Chest deflection V^*C	34 0.31	1.6	30.98 0.26	2.204
Pubic symphysis force (kN)	4.067	2.58	4.0	2.667
HIC	229.4	4	209.8	4
Total score		12.2		12.9

In general, the errors between the optimum results of response surface and those of reanalysis are acceptable. Even with one iteration, the predictions are reasonable good, compared with the reanalysis results. After three iterations, the errors of weight, velocities, forces, and rib deflections are within 1%, 2%, 3.6% and 5.3 %, respectively. These results show that for the side impact finite element model, the weight is reduced by 5.5 kg and the overall safety performance is better.

The statistical information corresponding to the input variables is required for the robustness assessment. In this study, all the variables were assumed to have a Gaussian normal distribution. The mean value for each variable was set to be the same as the optimal design. The standard deviation and mean value for each variable are listed in Table 5.

Table 5 Mean and standard deviation for all the factors.

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}
Mean μ	0.608	1.09	0.5	1.5	0.5	0.5	0.975	0.345	0.345	0	0
Std dev σ	0.018	0.029	0.015	0.045	0.027	0.012	0.023	0.03	0.03	10	10
σ/μ (%)	3	3	3	3	3	3	3	3	3		

Robustness assessment is performed by constructing an empirical cumulative distribution function (CDF) of the response variable generated from the Monte Carlo method. A random number generator that selects values for each random variable with a frequency proportional to the shape of the corresponding probability distribution. Usually 1000 to 10 000 samples are needed for a good representation of the response probability distribution. Without using the response surface, this task would be computationally excessive if not impossible. In this study, the stochastic simulation of the benchmark problem consists of 1000 independent samples with a given distribution. It takes less than 5 minutes for each response on an HP workstation.

Table 6 gives the level of confidence interval of the optimum design. It is noted that although the deterministic optimum design met all the design targets, both dummy chest deflection and pubic symphysis force, with the 90% confidence interval, violated design constraints when uncertainties are considered. This result indicates that in real world vehicle side impact test, there are more than 10% chance to violate the design targets.

Table 6 Robustness assessment.

	Nominal value	Confidence interval				
		70%	85%	90%	95%	99%
Weight (kg)	23.59	23.79	23.89	23.98	24.03	24.07
Abdomen load (kN)	0.55	0.56	0.57	0.57	0.58	0.59
Rib deflection (mm)	30.98	31.04	31.15	31.28	31.43	31.56
	27.49	27.99	28.6	29.0	29.4	29.8
	30.98	31.98	33.4	33.9	34.3	35.1
V^*C (m/s)	0.25	0.25	0.26	0.26	0.27	0.28
	0.21	0.22	0.23	0.23	0.24	0.25
	0.27	0.28	0.30	0.31	0.32	0.34
Pubic symphysis force	4.0	4.0	4.0	4.1	4.1	4.1

4 Reliability based design optimization

In engineering design, the deterministic design optimization model has been widely used to systematically reduce the cost and improve quality. However, the existence of uncertainties in either manufacturing process or engineering simulations calls for a robust design. The definition of robust design may differ in many applications. Here, it refers to selecting the optimal control factors so that the safety performance is the least sensitive to the noise factors. Several approaches for achieving a robust design have been developed. Mavris and Bandte (1997) proposed an approach for the robust design of multi-constraint and multi-objective problems by linking the response surface

methodology with the Monte Carlo simulations. An alternative for the robust system parameter design can be formulated by using a reliability based design optimization (RBDO) model (Tu *et al.* 1999).

In the robust system parameter design, the RBDO model is defined to identify the optimal design that not only optimise the performance (minimise or maximise one or more objectives), but also satisfy the constraints on the maximum reliability. The deterministic optimization problem in the previous section is converted to a reliability-based optimization problem by adding random variables and changing the deterministic constraints to the probabilistic reliability ones. The reliability-based optimization of vehicle side impact then is formulated as follows:

Minimise Weight

Subject to Prob {Abdomen load $\leq$ 1.0 kN} ε 90%

Prob {$V^*C \leq$ 0.32 m/s}ε 90%

Prob {D_{urd} (upper rib deflection) $\leq$ 35 mm}ε 90%

Prob {D_{mrd} (middle rib deflection) $\leq$ 35 mm}ε 90%

Prob {D_{lrd} (lower rib deflection) $\leq$ 35 mm} ε 90%

Prob {F (pubic symphysis force) $\leq$ 4.0 kN ε 90%

Prob {$V_{\text{B-Pillar}}$ (velocity of B-pillar at middle point) $\leq$ 10.0 mm/ms}ε 90%

Prob {$V_{\text{front door}}$ (velocity of front door at B-pillar) $\leq$ 17.50 mm/ms}ε 90%

Standard deviations Gauges and materials: 3%

Barrier height and hitting position: 10 mm

In the side impact CAE model, all random variables (gauges, material yield stress, barrier height and hitting position) are assumed to be normal distributed around their nominal value. The RBDO model requires calculating the reliability of the responses. There are several approaches that can be adopted for the probabilistic constraint evaluation (Mavris and Bandte, 1997). The Monte Carlo simulation combined with RSM is employed for both reliability calculation and optimization. Using reliability analysis method within a reliability-based optimization approach is considered to be a double-loop method. A double-loop method is usually considered to be computational expensive and time consuming. Since the surrogate models are used in this study, it takes about 30 minutes in HP workstation to perform the RBDO. The advantage of using Monte Carlo simulation is that it can easily handle a large number of design variables.

The results of the robust design for side impact is summarised in Table 7 and the side impact performance and the rating score are given in Table 8. These results show that for a given level of probability, the robust design yields a minimum objective function value and also satisfies all imposed constraints. For the robust design, the vehicle weight is reduced by 3.58 kg and the safety rating score is increased by 1.15. The optimal deterministic and robust designs of the side impact finite element model along with the side constraints of the variables are summarised in Table 9.

Table 7 Robust design solution summary.

Response	Performance		90% Confidence interval	
	Baseline	RBDO	RBDO	Constraints
Weight (kg)	29.18	25.60	26.37	—
$V_{\text{B-pillar}}$	9.9	9.28	9.6	≤ 10 mm/ms
$V_{\text{front door}}$	15.7	15.31	17.2	≤ 17.5 mm/ms
AB force	0.66	0.456	0.503	≤ 1.0 kN
V^*C (up)	0.22	0.222	0.251	≤ 0.32 mm/ms
V^*C (mid)	0.21	0.196	0.231	≤ 0.32 mm/ms
V^*C (low)	0.31	0.260	0.29	≤ 0.32 mm/ms
D_{up}	28.53	27.3	34.31	≤ 36 mm
D_{mid}	28.99	29.2	31.43	≤ 36 mm
D_{low}	33.95	29.9	33.67	≤ 36 mm
Pubic symphysis force	4.0	3.80	3.893	≤ 4.00 kN

Table 8 Safety rating score of robust design.

Performance	Baseline		RBDO	
	Design	Rating score	Design	Rating score
Weight (kg)	29.18	—	25.60	—
Abdomen force(kN)	0.66	4	0.456	4
Chest Deflection (mm)	34.0	1.6	29.9	2.42
V^*C (m/s)	0.31		0.26	
Pubic symphysis force (kN)	4.07	2.58	3.80	2.93
HIC	229.4	4	203.7	4
Total score		12.2		13.35

Table 9 Optimal designs and RBDO of side impact model.

Design variable	Baseline	Deterministic optimization	RBDO	Constraints
x_1	1.0	0.5	0.776	$0.5\,x_1^0 \le x_1 \le 1.5\,x_1^0$
x_2	1.0	1.36	1.2	$0.5\,x_2^0 \le x_1 \le 1.5\,x_2^0$
x_3	1.0	0.5	0.896	$0.5\,x_3^0 \le x_1 \le 1.5\,x_3^0$
x_4	1.0	1.202	1.467	$0.5\,x_4^0 \le x_1 \le 1.5\,x_4^0$
x_5	1.0	0.5	0.55	$0.5\,x_{50} \le x_1 \le 1.5\,x_5^0$
x_6	1.0	1.12	1.44	$0.5\,x_6^0 \le x_1 \le 1.5\,x_6^0$
x_7	1.0	0.5	0.55	$0.5\,x_7^0 \le x_1 \le 1.5\,x_7^0$
x_8	MS	HSS	HSS	x_8: MS or HSS
x_9	MS	MS	HSS	x_9: MS or HSS

MS: Mild steel
HSS: High strength steel

5 Conclusions

A response surface based safety optimization and robustness process is presented. The process integrates many state-of-the-art technologies, including the optimal Latin hyper cube sampling, stepwise regression, numerical optimization, and the Monte Carlo method. The process has been successfully demonstrated for the side impact design.

The results show that for the problem with N factors, $3N$ simulation matrix, which is generated from the optimal Latin hyper cube sampling method, can obtain a satisfactory approximation. An illustrative side impact example is given. The example shows that the optimization results for both the deterministic and the robust designs are promising. For the optimal deterministic design, the total vehicle weight is reduced by 5.5 kg and the safety rating score is increased by 0.7 points. For the RBDO model, the vehicle total weight is reduced by 3.6 kg and the safety rating score is increased by 1.15 points with a 90% confidence level.

Although side impact is a highly nonlinear event, this study shows that the proposed process can obtain reasonably good results for both the deterministic and the robust designs.

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References

Blumhardt, R. (1999) 'FEM – Crash Simulation and Optimization', *OPTICON'99*, California.

Chargin, M; and Miura, H. (1999) 'Computer Aided Engineering for Improved Vehicle Crashworthiness', Poster paper at *Optimization in Industry – II*, Banff, Canada, June 6–11.

Choi, K. K. and Cho, S. (1998) 'Design Sensitivity Analysis and optimization of Nonlinear Structural Dynamics Using DYNA3D' AIAA-98-4721, *7th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization*, Missouri, pp. 148–158.

Currin, C., Mitchell, T., Morris, M., Ylvisaker, D. (1991) 'Bayesian Prediction of Deterministic Function, with Applications to the Design and Analysis of Computer Experiments', *Journal of the American Statistical Association*, Vol 86, pp. 953–963.

Draper, N. and Smith, H. (1966) *Applied Regression Analysis*, John Wiley & Sons.

Mavris, D. and Bandte, O. (1997) 'A Probabilistic Approach to Multivariate Constrained Robust Design Simulation', *SAE 97-5508*.

RADIOSS (1998) *User Manual Version 4.1*, MECALOG SARL, France.

Schramm, U. and Thomas, H. (1998) 'Crashworthiness Design Using Structural Optimization', AIAA-98-4729, 7th *AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and optimization*, Missouri, pp. 197–205.

Sobieski, J., Kodiyalam, S., and Yang, R.J. (2000) 'Optimization of Car Body under Constraints of Noise, Vibration, and Harshness (NVH), and Crash', *41st AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, Atlanta, Georgia, 3–6 April.

Stander, N. (1999) 'Crashworthiness Technology Using Response Surface Methodology and Massively Parallel Programming', Poster paper at *Optimization in Industry – II*, Banff, Canada, June 6–11.

Sudjianto, A., Juneja, L. and Agrawal, A. (1998) 'Computer Aided Reliability and Robustness Assessment', *Int. J. of Reliability, Quality and Safety Engineering*, Vol. 5.

Tu, J., Choi, K.K. and Park, Y. H. (1999) 'A New Study on Reliability Based Design Optimization', *Journal of Mechanical Design*, December, Vol 121.

Yang, R. J., Tseng, L., Nagy, L. and Cheng, J. (1994) 'Feasibility Study of Crash Optimization', *ASME,* Vol. 69-2, pp. 549–556.

Yang, R. J., Gu, L., Liaw, L., Gearhart, Tho, C. H. (2000) 'Approximations for Safety Optimization of Large Systems', *ASME DTEC Conference*, Baltimore, Sept 10–13.

Yu, Q. and Yajima, H. (2000) 'Influence on injury criteria of occupant restraint system', *SAE-2000-01-0623.*