International Journal of Automotive Technology, Vol. 8, No. 1, pp. 93−102 (2007)

1229−9138/2007/032−12

SIZE OPTIMIATION OF AN ENGINE ROOM MEMBER FOR CRASHWORTHINESS USING RESPONSE SURFACE METHOD

S. OH[1)*], B.-W. YE[1)] and H.-C. SIN[1)]

[1)]School of Mechanical and Aerospace Engineering, Seoul National University, Seoul 151-744, Korea

(Received 7 August 2006; Revised 11 January 2007)

ABSTRACT−The frontal crash optimization of an engine room member using the response surface method was studied. The engine room member is composed of the front side member and the sub-frame. The thicknesses of the panels on the front side member and the sub-frame were selected as the design variables. The purpose of the optimization was to reduce the weight of the structure, under the constraint that the objective quantity of crash energy is absorbed. The response surface method was used to approximate the crash behavior in mathematical form for optimization procedure. To research the effect of the regression method, two different methodologies were used in constructing the response surface model, the least square method and the moving least square method. The optimum with the two methods was verified by the simulation result. The precision of the surrogate model affected the optimal design. The moving least square method showed better approximation than the least square method. In addition to the deterministic optimization, the reliability-based design optimization using the response surface method was executed to examine the effect of uncertainties in design variables. The requirement for reliability made the optimal structure be heavier than the result of the deterministic optimization. Compared with the deterministic optimum, the optimal design using the reliability-based design optimization showed higher crash energy absorption and little probability of failure in achieving the objective.

KEY WORDS : Crashworthiness, Response surface method (RSM), Moving least square method, Deterministic design optimization, Reliability based design optimization (RBDO)

1. INTRODUCTION

Studies on vehicle crashworthiness design has been done for decades. With the increase in the standard in vehicle safety requirements from government and consumer, the design for crashworthiness became a major task in the vehicle development process.

For more safe crash behavior, it is helpful that the front structure of vehicle absorbs more crash energy in the initial stage of crash event. The front side member and the sub-frame are the main components of the vehicle front structure that absorbs a major portion of the crash energy in a full-vehicle crash (Gonzalez *et al.*, 2005). So the geometric shape and the size of these components greatly affect the crashworthiness of a vehicle.

The geometric shape of the front structure is, however, restricted by various constraints: engine/transmission mount position, suspension assembly, and so on. Thus it is a relatively difficult task to optimize the shape of the structure. It is easier and more efficient to optimize the thicknesses of components to increase the energy absorption.

The front side member and the sub-frame are composed of several thin-walled sections which are spot-welded or arc-welded with each other. In general, as the overall thickness increases, the energy absorbing increases as well. But the increase of thicknesses makes the vehicle heavier, potentially bringing about other disadvantages. So necessary studies need to be conducted on the design optimization to improve the energy absorption while reducing the weight of vehicle.

However, there are some difficulties in performing a design optimization for the crashworthiness problems due to the limitations of computational resource and the enormous analysis time consumed. Another issue is related to the fact that structural optimization often requires gradients of the objective and constraints to determine a search direction in optimization procedure. For vehicle crash problems, the objective and the constraints functions are often too noisy and it is difficult to find the gradient due to its severe nonlinearity. Hence, it is critical that a response surface model (i.e. approximation) be constructed a priori using the results from a number of actual crash simulations for the crashworthiness optimization.

Many researchers have investigated the problem of applying the response surface method to crashworthiness problems. Redhe *et al.* (2002) studied the method of

Corresponding author. e-mail: ttuck2@snu.ac.kr

determining the efficient number of experimental points when using the response surface method in crashworthiness problems. Avalle *et al.* (2002) applied the response surface method to the optimization of thin-walled column with circular and rectangular cross-section. Gu *et al.* (2005) used the response surface method for optimally controlling the crash-pulse. Kim *et al.* (2005) conducted optimization of aluminum space frame using the response surface method.

Once the appropriate response surface model is constructed, the optimal design can be obtained by using various structural optimization methods. However some problems remain unresolved. There are some uncertainties which exist in real systems and they have not yet been considered in computer simulation. Even the small variance of thicknesses, crash angle and the geometric imperfection in manufacturing process can change the crash behavior of vehicle dramatically (Qi *et al.*, 2005). Consequently, obtaining the deterministic optimum designs without considering these uncertainties can lead to unreliable designs. So, in recent times, the reliability-based design optimization (RBDO) technique is widely used to address these uncertainties.

Youn *et al.* (2004) used the reliability-based design optimization for a vehicle side impact problem with a response surface method. Riha *et al.* (2004) studied the stochastic approach for the vehicle-to-vehicle frontal offset crash model. Choi *et al.* (2005) applied the reliability-based design optimization to the optimization of an automotive suspension system.

In this paper, the deterministic optimization and the reliability based design optimization for the front side member and the sub-frame was conducted to increase the crash energy absorption and to reduce the vehicle weight. For the optimization procedure, the response surface model was constructed using several simulations at selected sampling points. Two different methods, the least square method and the moving least square method, were used to generate the response surface model, and the results were compared.

2. RESPONSE SURFACE METHODOLOGY

2.1. Sampling Method

One major factor that influences the quality of the response surface model is the selection of the data points, or the so-called sampling technique, that is used to create the surrogate model. The Central Composite Design (CCD) is the most popular class of second-order designs (Myers and Montgomery, 1995). This is a composite of two-level full factorial design with star points located at the extremes of the region of interest. The CCD has a disadvantage in that it requires a large number of experiments to be done as the design variable increases. But if the optimum exists near the edge of design area, CCD can offer more accurate result than other modern sampling methods (Barros *et al.*, 2004). The number of sampling points in CCD is $1+2n+n^2$ where n is the number of design variables.

2.2. Least Square Method

The least square method is the most widely used method to create the surrogate model because it is easy to use. The least square approximation can be formulated as

$$\hat{g}(\mathbf{d})=\sum_{i=1}^{NB} h_i(\mathbf{d})a_i \equiv \mathbf{h}^T(\mathbf{d})\mathbf{a} \tag{1}$$

where NB is the number of terms in the basis, **h** is the monomial basis vector, **d** is the design parameter.

To compute the coefficient vector **a**, a residual is defined as

$$E(\mathbf{d})=\sum_{i=1}^{NS} [\hat{g}(\mathbf{d})-g(\mathbf{d}_I)]^2 \tag{2}$$

where NS is the number of sample points. The minimization of the residual E by $\partial E/\partial \mathbf{a}=0$ yields the coefficient **a**.

2.3. Moving Least Square Method

Since Lancaster and Salkauskas (1986) introduced the moving least square (MLS) method, it has been successfully applied to the mesh-free method (Belytscheko, 1994) and the reliability-based design optimization (Choi and Youn, 2001).

The moving least square approximation can be formulated as

$$\hat{g}(\mathbf{d})=\sum_{i=1}^{NB} h_i(\mathbf{d})a_i(\mathbf{d}) \equiv \mathbf{h}^T(\mathbf{d})\mathbf{a}(\mathbf{d}) \tag{3}$$

The approximation has the non-constant coefficients which differ from that of the least square method. The local approximation in the moving least square method is given by

$$\hat{g}(\mathbf{d},\mathbf{d}_I)=\sum_{i=1}^{NB} h_i(\mathbf{d}_I)a_i(\mathbf{d}) \equiv \mathbf{h}^T(\mathbf{d}_I)\mathbf{a}(\mathbf{d}) \tag{4}$$

where NB is the number of terms in the basis, NS is the number of sample points, **h** is the basis vector, $\mathbf{d}_I$ is the sample point, and **a**(**d**) is the coefficient vector of the moving least square approximation.

To compute the coefficient vector **a**(**d**), a weighted residual is defined as

$$E(\mathbf{d})=\sum_{i=1}^{NS} w(\mathbf{d}-\mathbf{d}_I)[\hat{g}(\mathbf{d},\mathbf{d}_I)-g(\mathbf{d}_I)]^2$$
$$=\sum_{i=1}^{NS} w(\mathbf{d}-\mathbf{d}_I)\left[\sum_{i=1}^{NB} h_i(\mathbf{d}_I)a_i(\mathbf{d})-g(\mathbf{d}_I)\right]^2 \tag{5}$$

where $w(\mathbf{d}-\mathbf{d}_I)$ is a weight function with a compact support which gives a higher weight to the sampling points closer to the design points. The unknown coefficients $\mathbf{a}(\mathbf{d})$ at any given point are determined by minimizing the weighted residual E by $\partial E/\partial \mathbf{a}=0$.

An appropriate support size at any point $\mathbf{d}$ is selected so that a sufficient number of neighboring data points is included to avoid singularity. A variable weight over the compact support provides local averaging to the response approximated by the moving least square method.

3. OPTIMIZATION METHODOLOGY

3.1. Deterministic Optimization

The general constrained minimization problem can be stated as follows

$$\text{minimize Cost}(\mathbf{d})$$
$$\text{subject to } G_i(\mathbf{d})\le 0$$
$$i=1,\ldots,\text{NC} \quad \mathbf{d}^L \le \mathbf{d} \le \mathbf{d}^U,\ \mathbf{d}\in R^{\text{NDV}} \tag{6}$$

where Cost($\mathbf{d}$) is the objective and $G_i(\mathbf{X})$ is the constraints; $\mathbf{d}$ is the design variables. NC is the number of constraints; NDV is the number of design variables.

There are several methodologies for solving the problem: linear programming (LP), sequential linear programming (SLP), and sequential quadratic programming (SQP), genetic algorithms (GA), and so on. In this study, the sequential quadratic programming method (Arora, 1989) was used for optimization.

3.2. Reliability Based Design Optimization

In system parameter design, the RBDO model can generally be defined as

$$\text{minimize Cost}(\mathbf{d})$$
$$\text{subject to } P(G_i(\mathbf{X})\le 0)-\Phi(-\beta_{t_i})\le 0$$
$$i=1,\ \ldots,\ \text{NC}$$
$$\mathbf{d}^L \le \mathbf{d} \le \mathbf{d}^U,\ \mathbf{d}\in R^{\text{NDV}} \text{ and } \mathbf{X}\in R^{\text{NRV}} \tag{7}$$

where NRV is the number of random parameters; $\mathbf{d}=\mu(\mathbf{X})$ is the design vector; $\mathbf{X}$ is the random vector; $P(\bullet)$ is the probability that a corresponding event will occur; Φ is a normal cumulative distribution function; β_{t_i} is the target reliability value which is used to describe the objective reliability.

The main difference between the RBDO and the deterministic design optimization lies in probabilistic constraint evaluation of equation (8).

$$P(G_i(\mathbf{X})\le 0)=F_{G_i}(0)\le\Phi(-\beta_{t_i})$$
$$F_{G_i}(0)=\int_{(G_i(\mathbf{X})\le 0)}\cdots\int f_X(\mathbf{x})d\mathbf{x} \tag{8}$$

where F_{G_i} is a cumulative distribution function.

The evaluation of probabilistic constraints requires a reliability analysis to be carried out and this involves the multiple-integration of the joint probability density function f_x.

Some approximate probability integration methods have been developed to provide efficient solutions, such as the first-order reliability method (FORM) and the asymptotic second-order reliability method (SORM) (Madsen *et al.*, 1986) which has a rotationally invariant measure as the reliability. FORM often provides adequate accuracy and is widely used for RBDO applications.

3.2.1. first-order reliability analysis

There are two different approaches in the reliability evaluation method: the reliability index approach (RIA) (Enevoldsen and Sorensen, 1994) and the performance measure approach (PMA) (Tu and Choi, 1999). Between the two, PMA is more effective and shows robust characteristics in numerical properties (Choi and Youn, 2001). The PMA procedure is as follows:

For invariant property, the random parameter X is transformed into standard normal random parameter U and the performance function $G(\mathbf{X})$ in X-space is mapped onto $G(\mathbf{U})$ in U-space.

The probabilistic constraint in equation (8) can be expressed as shown bellow by the inverse transformation.

$$G_{p_i}=F_{G_i}^{-1}(\Phi(-\beta_{t_i}))\ge 0 \tag{9}$$

The first-order probabilistic performance measure G_{p_i} can be obtained from the nonlinear optimization problem in U-space, defined as

$$\text{minimize } G(\mathbf{U})$$
$$\text{subject to } \|\mathbf{U}\|=\beta_t \tag{10}$$

where the optimum point on the target reliability surface is identified as the most probable point (MPP) with a prescribed reliability target. In iterative optimization process, only the direction vector needs to be determined by exploring the spherical equality constraint.

The numerical procedure of the RBDO process is described in Figure 1. The box in the right-hand side represents the reliability analysis procedure which evaluates the probabilistic constraints.

3.2.2. MPP search method

In order to find the minimum value of equation (10), Youn *et al.* (2003) proposed the hybrid mean value (HMV) method which selectively combines the advanced mean value (AMV) method (Wu *et al.*, 1990) and the conjugate mean value (CMV) method (Choi and Youn, 2001).

To find the minimum point (i.e., the MPP), the AMV method iteratively updated the steepest descent direction vector at the probable point $\mathbf{u}_{\text{AMV}}^{(k)}$ as

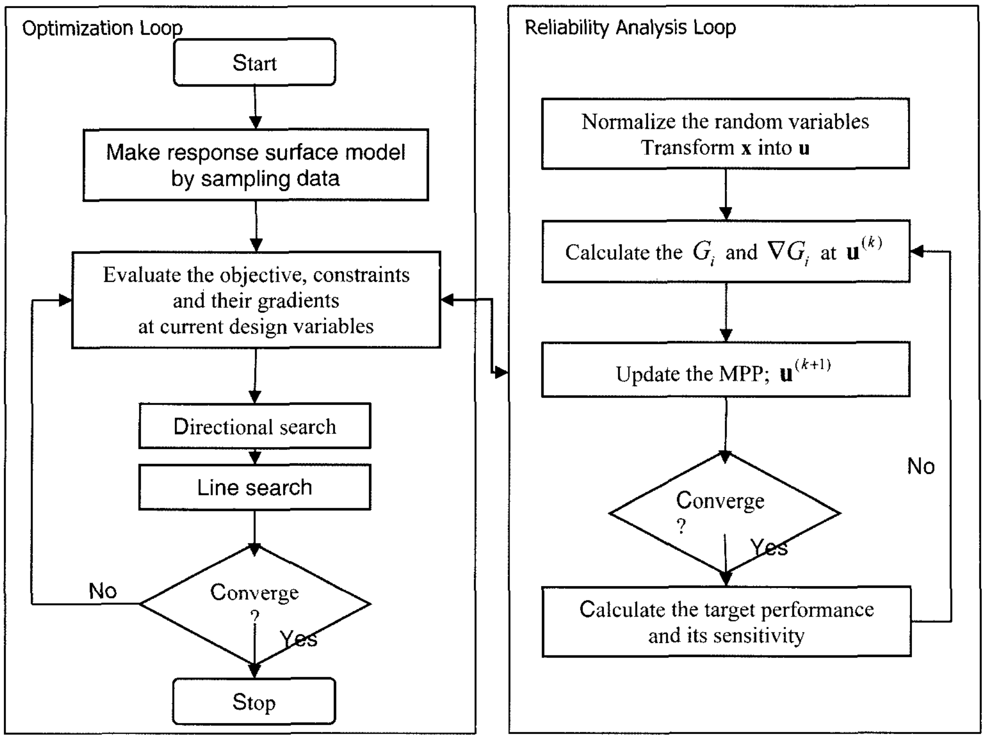


Figure 1. Flow chart of the reliability based design optimization procedure.

$$\mathbf{u}_{\mathrm{AMV}}^{(0)}=0 \text{ and } \mathbf{u}_{\mathrm{AMV}}^{(k+1)}=\beta_t \mathbf{n}(\mathbf{u}_{\mathrm{AMV}}^{(k)})$$

$$\text{where } \mathbf{n}(\mathbf{u}_{\mathrm{AMV}}^{(k)})=-\frac{\nabla_U G(\mathbf{u}_{\mathrm{AMV}}^{(k)})}{\left\|\nabla_U G(\mathbf{u}_{\mathrm{AMV}}^{(k)})\right\|} \tag{11}$$

But when $G(\mathbf{U})$ is a concave function, the AMV method exhibits instability and inefficiency since it only updates the direction using the current point. So the CMV method was proposed for the concave function which combines $\mathbf{n}(\mathbf{u}_{\mathrm{CMV}}^{(k-2)})$, $\mathbf{n}(\mathbf{u}_{\mathrm{CMV}}^{(k-1)})$ and $\mathbf{n}(\mathbf{u}_{\mathrm{CMV}}^{(k)})$ for the next steepest descent direction. Like as,

$$\mathbf{u}_{\mathrm{CMV}}^{(0)}=0,\ \mathbf{u}_{\mathrm{CMV}}^{(1)}=\mathbf{u}_{\mathrm{AMV}}^{(1)},\ \mathbf{u}_{\mathrm{CMV}}^{(2)}=\mathbf{u}_{\mathrm{AMV}}^{(2)}$$

$$\mathbf{u}_{\mathrm{CMV}}^{(k+1)}=\beta_t \frac{\mathbf{n}(\mathbf{u}_{\mathrm{CMV}}^{(k)})+\mathbf{n}(\mathbf{u}_{\mathrm{CMV}}^{(k-1)})+\mathbf{n}(\mathbf{u}_{\mathrm{CMV}}^{(k-2)})}{\left\|\mathbf{n}(\mathbf{u}_{\mathrm{CMV}}^{(k)})+\mathbf{n}(\mathbf{u}_{\mathrm{CMV}}^{(k-1)})+\mathbf{n}(\mathbf{u}_{\mathrm{CMV}}^{(k-2)})\right\|}$$

$$\text{where } \mathbf{n}(\mathbf{u}_{\mathrm{CMV}}^{(k)})=-\frac{\nabla_U G(\mathbf{u}_{\mathrm{CMV}}^{(k)})}{\left\|\nabla_U G(\mathbf{u}_{\mathrm{CMV}}^{(k)})\right\|} \tag{12}$$

However, the CMV method is inefficient for the convex function. To overcome this, the HMV method investigates the function type at current point by checking the sign of the equation (13).

$$\varsigma^{(k+1)}=(\mathbf{n}^{(k+1)}-\mathbf{n}^{(k)})\cdot(\mathbf{n}^{(k)}-\mathbf{n}^{(k-1)}) \tag{13}$$

Once the performance function type is identified, either AMV or CMV is adaptively selected for deciding the next steepest direction vector.

4. OPTIMIZATION RESULT

4.1. Model Description

The object model of optimization is illustrated in Figure 2. A full-vehicle finite element (FE) model needs enormous computing power and analysis time. So, in this study, a part model composed of the front side member, the sub-frame, and the lower arm was used. The used FE model consisted of 33430 shell elements and 33335 nodes. The lumped mass was added to the center of gravity of engine /transmission and connected to the mount position at the front side member and the sub-frame. The vehicle weight was added to the center of gravity of full-vehicle and connected to the rear parts of the model. In the FE

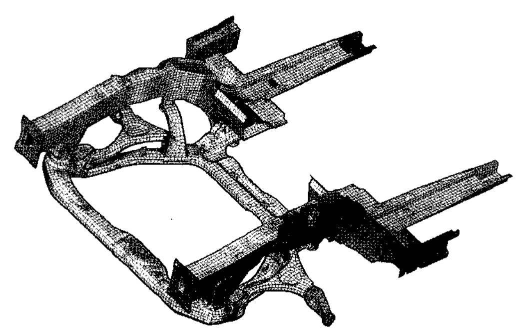
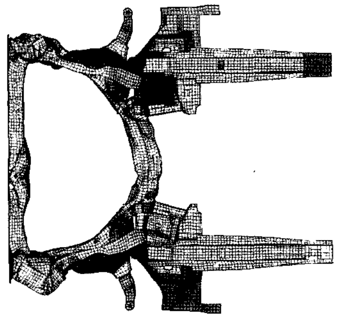
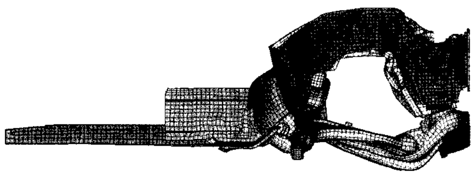


Figure 2. the object model for optimization.



(a) top view



(b) side view

Figure 3. Deformed shape at 30ms: (a) top view (b) side view.

simulation, the model had an initial velocity of 14 m/s and impacts to rigid wall at full front. This model was analyzed during 30 ms using an explicit nonlinear finite element code PAM-CRASH. The deformed shape is shown in Figure 3.

The total weight of the front side member and sub-frame of initial model is 23.41 kg and the internal energy which is the crash energy absorbed by the structure is 8352 J at 30 ms.

Four thickness values (t_1-t_4) described in Table 1 were selected as the design variables in the optimization. The front side member and the sub-frame are composed of these four thin-walled panels, and these thicknesses influence the crash behavior of the vehicle significantly.

To construct the response surface model, a simulation was conducted at 25 sampling points by the central composite design method. Table 2 shows the thicknesses of the design variables at each sample point and the internal energy value at 30 ms obtained by simulation.

4.2. Result of the Deterministic Optimization

The model of deterministic optimization is as follows:

Table 2. Simulation results for sample points.

Exp. no.	t_1 (mm)	t_2 (mm)	t_3 (mm)	t_4 (mm)	Internal energy (J)
1	1.80	1.80	2.30	2.00	8352
2	1.50	1.50	2.00	1.70	7590
3	2.10	1.50	2.00	1.70	7738
4	1.50	2.10	2.00	1.70	8499
5	1.50	1.50	2.60	1.70	7812
6	1.50	1.50	2.00	2.30	7770
7	2.10	2.10	2.00	1.70	8604
8	2.10	1.50	2.60	1.70	7972
9	2.10	1.50	2.00	2.30	7913
10	1.50	2.10	2.30	1.70	8727
11	1.50	2.10	2.00	2.30	8712
12	1.50	1.50	2.60	2.30	7991
13	2.10	2.10	2.60	1.70	8803
14	2.10	2.10	2.00	2.30	8778
15	2.10	1.50	2.60	2.30	8135
16	1.50	2.10	2.60	2.30	8930
17	2.10	2.10	2.60	2.30	8992
18	1.38	1.80	2.30	2.00	8166
19	2.22	1.80	2.30	2.00	8458
20	1.80	1.38	2.30	2.00	7679
21	1.80	2.22	2.30	2.00	8893
22	1.80	1.80	1.88	2.00	8199
23	1.80	1.80	2.72	2.00	8505
24	1.80	1.80	2.30	1.58	8223
25	1.80	1.80	2.30	2.42	8473

$$\begin{aligned} &\min \ \text{weight}(t_1,t_2,t_3,t_4) \\ &\text{subject to } E_{\text{internal}}\ (t_1,t_2,t_3,t_4) \geq E_{\text{target}} \\ &t_L \leq t_i \leq t_U \end{aligned} \quad (14)$$

where weight(t_1,t_2,t_3,t_4) is the total weight of front side member and sub-frame; E_{target} is the objective internal energy value which is absorbed by the front side member and sub-frame; t_L, t_U is the lower and upper bound of thickness value.

The objective is to find the optimum thickness set which weighs the least and absorbs the objective internal

Table 1. Design variables.

	Design variable	Initial value (mm)	Lower bound	Upper bound
t_1	Front side member outer thickness	1.8	1.5	2.1
t_2	Front side member inner thickness	1.8	1.5	2.1
t_3	Sub-frame upper thickness	2.3	2.0	2.6
t_4	Sub-frame lower thickness	2.0	1.7	2.3

energy.

4.2.1. Deterministic optimization result using the least square method

The deterministic design optimization was performed for the problem stated in equation (14) using sequential quadratic programming. The least square method was used to create the response surface model. Second-order regression model of equation (15) was constructed using the sampling data of Table 2.

$$E_{\text{internal}}(\mathbf{t})=b_0+\sum_{i=1}^{4} b_i t_i+\sum_{i=1}^{4} b_{ii} t_i^2+\sum_{i=1}^{3}\sum_{j=i+1}^{4} b_{ij} t_i t_j \quad (15)$$

Six different values from 8,400 J to 8,900 J with the increment of 100 were selected as the objective internal energy value E_{target}. These values are greater than the internal energy value of the initial model. The simulation was conducted with the optimal thicknesses for each case to verify the mathematical result.

Table 3. Deterministic optimization result using the least square method.

E_{target}	t_1	t_2	t_3	t_4	Mass (kg)	Internal energy (J)
8400	1.500	2.013	2.000	1.700	21.895	8410
8500	1.500	2.080	2.000	1.700	22.224	8514
8600	1.500	2.100	2.177	1.700	22.688	8573
8700	1.500	2.100	2.441	1.700	23.248	8670
8800	1.750	2.100	2.600	1.700	24.450	8768
8900	2.100	2.100	2.600	1.700	25.638	8803

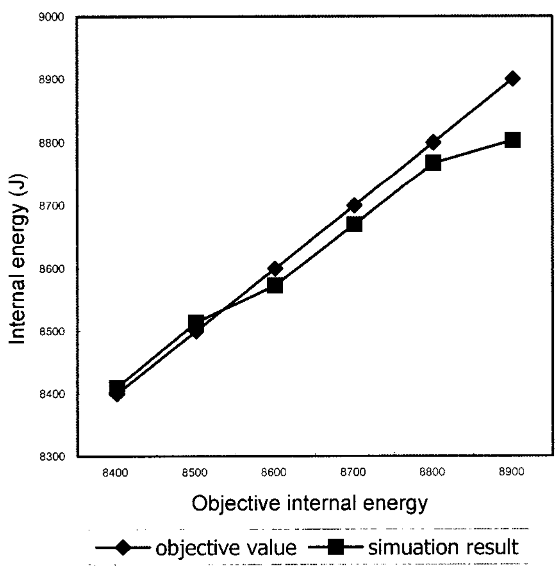


Figure 4. Simulation result with the design using the least square method.

The optimal thicknesses about the six objective internal energy values and the simulation result with each optimum are listed in Table 3. Figure 3 shows the objective internal energy value and the internal energy obtained by the simulation with the optimization result to check the difference between them.

In the cases where the objective internal energy is less than 8,800 J, the simulation with the optimal thicknesses shows approximate result to the objective value as can be seen in Figure 4. In the case where the objective internal energy is 8,900 J, on the other hand, the simulation with the optimization result failed to achieve the objective internal energy value.

It can be yielded from the results that in some area of the design domain (in this case, at the boundary of the design area), the least square method can not offer sufficient approximation of the crash behavior. So, there is a possibility that the optimum with the response surface model using the least square method may fail to achieve the objective even though it offers successful result in some area.

4.2.2. Deterministic optimization result using the moving least square method

In this section, the response surface model was generated by the moving least square method. Second-order regression model with non-constant coefficients in equation (16) was constructed using the sampling data provided in Table 2 and used in the optimization procedure.

$$E(\mathbf{t})=b_0(\mathbf{t})+\sum_{i=1}^{4} b_i(\mathbf{t}) t_i+\sum_{i=1}^{4} b_{ii}(\mathbf{t}) t_i^2+\sum_{i=1}^{3}\sum_{j=i+1}^{4} b_{ij}(\mathbf{t}) t_i t_j \quad (16)$$

Six objective internal energy values which are the same as values used in the previous section were used in optimization.

The optimal thicknesses about the six objective internal energy values and the simulation result for each optimum are described in Table 4. Figure 4 shows the objective internal energy value and the internal energy obtained by the simulation with the optimization result.

Table 4. Deterministic optimization result using the moving least square method.

E_{target}	t_1	t_2	t_3	t_4	Mass (kg)	Internal energy (J)
8400	1.500	2.011	2.000	1.700	21.883	8379
8500	1.500	2.079	2.000	1.700	22.209	8472
8600	1.500	2.100	2.161	1.702	22.656	8571
8700	1.500	2.100	2.322	1.859	23.265	8681
8800	1.500	2.100	2.500	1.980	23.848	8790
8900	1.500	2.100	2.600	2.214	24.453	8907

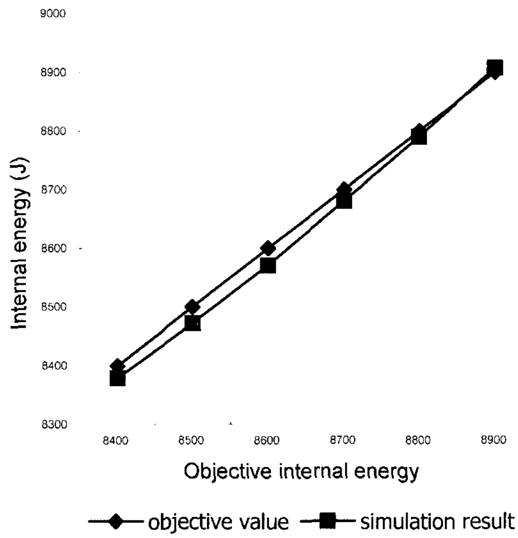


Figure 5. Simulation result with the optimal design using the moving least square method.

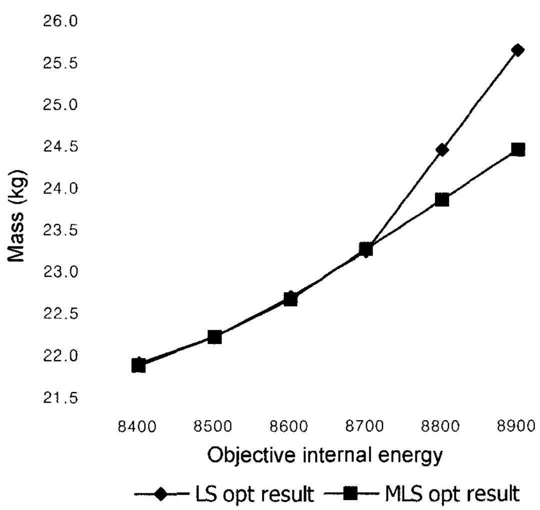


Figure 6. Weight of the optimal design.

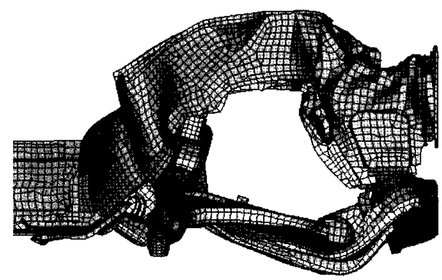
As can be seen in Figure 5, in every case, the simulation result with the optimal thicknesses achieved the objective internal energy value successfully. The optimization result using the moving least square method showed less weight than the result by the least square method in spite of the fact that it absorbed more internal energy.

In Figure 6. The weight of optimized design was compared between the least square method and the moving least square method.

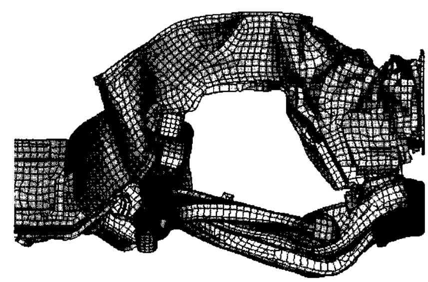
From the results, we can conclude that the moving least square method offers a more precise approximation for the whole design domain and the optimization using the appropriate response surface model shows a reliable result in crashworthiness design.

Table 5. Collapse distance of the optimal models.

E_{target}	Collapse distance (mm)	E_{target}	Collapse distance (mm)
8400	121.4	8600	132.8
8500	134.5	8700	133.5
8600	132.3	8800	134.0



(a)



(b)

Figure 7. Deformed shape at 30 ms : (a) the initial model (b) the optimal model with the objective internal energy value of 8,700J.

By the optimization, the weight of vehicle can be reduced by about 1.5 kg in comparison with the initial model for the same internal energy absorption. And the internal energy can be increased by about 350 J if we use the same weight as the initial model.

Figure 7 shows the collapse mode of the initial model and the optimal model with the objective internal energy value of 8,700 J. The optimal model induced more axial collapse of the front side member than the initial model. The collapse distances of optimal models were listed in Table 5. The collapse distance was measured for front 300 mm length of the front side member. The collapse distance of the initial model is 120 mm.

Compared with the initial model, the optimal model showed larger value of collapse distance in every case.

4.3. Result of the Reliability Based Design Optimization

In this section, RBDO was executed considering the uncertainty of the thickness.

The model of RBDO is as follows.

$$\min \text{ weight}(t_1,t_2,t_3,t_4)$$
$$\text{subject to } P(E_{\text{internal}}\ (t_1,t_2,t_3,t_4) \geq E_{\text{target}}) \geq P_s$$
$$t_L \leq t_i \leq t_U \quad (15)$$

where $P(E_{\text{internal}}(t_1,t_2,t_3,t_4) \geq E_{\text{target}})$ is the possibility that the internal energy absorption is greater than the objective internal energy value, and P_s is the target reliability value.

The same objective internal energy values of the previous section were used in RBDO as well. The four thickness variables were assumed to be the random variables with a deviation of 0.02. The normal distribution was assumed. RBDO was conducted for three increasing target reliabilities, P_s=90%, 99% and 99.865%. Because the moving least square method showed better performance as mentioned in the previous section, the response surface model was constructed by the moving least square method by using the data of Table 2.

Table 6. RBDO result with three target reliabilities.
(a) Target reliability of 90%

E_{target}	t_1	t_2	t_3	t_4	mass (kg)	internal energy (J)
8400	1.500	2.038	2.000	1.700	22.013	8413
8500	1.500	2.100	2.019	1.701	22.353	8506
8600	1.500	2.100	2.230	1.755	22.894	8617
8700	1.500	2.100	2.414	1.865	23.470	8717
8800	1.500	2.100	2.565	2.039	24.084	8830
8900	1.569	2.100	2.600	2.300	24.832	8945

(b) Target reliability of 99%

E_{target}	t_1	t_2	t_3	t_4	mass (kg)	internal energy (J)
8400	1.500	2.060	2.000	1.700	22.120	8438
8500	1.500	2.100	2.097	1.700	22.517	8537
8600	1.500	2.100	2.290	1.794	23.086	8650
8700	1.500	2.100	2.456	1.941	23.689	8756
8800	1.500	2.100	2.594	2.123	24.287	8871
8900	1.789	2.100	2.600	2.300	25.589	8978

(c) Target reliability of 99.865%

E_{target}	t_1	t_2	t_3	t_4	mass (kg)	internal energy (J)
8400	1.500	2.074	2.000	1.700	22.188	8465
8500	1.500	2.100	2.146	1.700	22.622	8559
8600	1.500	2.100	2.326	1.823	23.213	8671
8700	1.500	2.100	2.493	1.967	23.811	8784
8800	1.500	2.100	2.599	2.192	24.414	8899
8900	1.978	2.100	2.600	2.300	26.231	8981

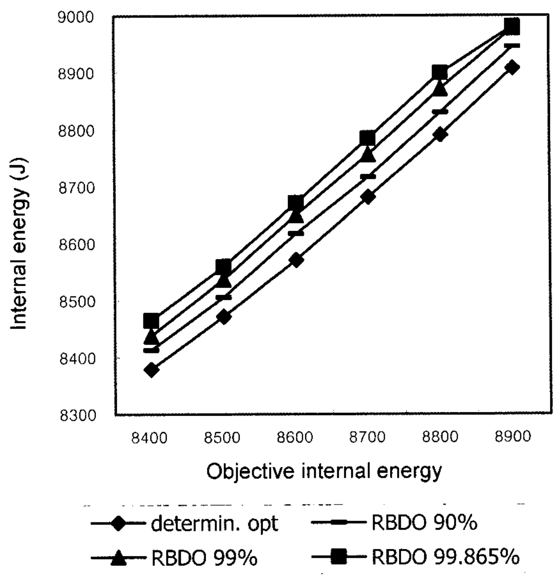


Figure 8. Simulation results of optimal designs of the deterministic optimization and RBDO.

The PMA method was applied to evaluate the probabilistic constraint in reliability analysis, and the HMV method was used for MPP search method.

The results of RBDO in Table 6 show larger values in internal energy absorption than those of the deterministic optimization. As the target reliability increases, the optimal design absorbs more internal energy. Figure 8 shows the internal energy values obtained by the four optimal designs: the deterministic optimization, RBDO with 90% reliability, RBDO with 99% reliability and RBDO with 99.865% reliability.

From the point of view of vehicle weight, however, RBDO demands comparatively larger weight due to the requirement of reliability. Figure 9 shows the weight of the optimal designs. It can be seen that the weight of the structure increases as the high reliability value is adopted in optimization.

Even in the most severe level of reliability, nevertheless, the optimal design in RBDO shows better performance than the initial design. The weight can be reduced by about 1.2 kg in comparison with the initial model for the same internal energy absorption. Other relatives the internal energy can be increased by about 300 J in using the same weight as the initial model.

In Figure 10, the three designs for the objective internal energy 8,700 J: the result of deterministic optimization, the result of RBDO with 90% target reliability, the result of RBDO with 99.865% target reliability, were compared in their cumulative probability distribution. The result of

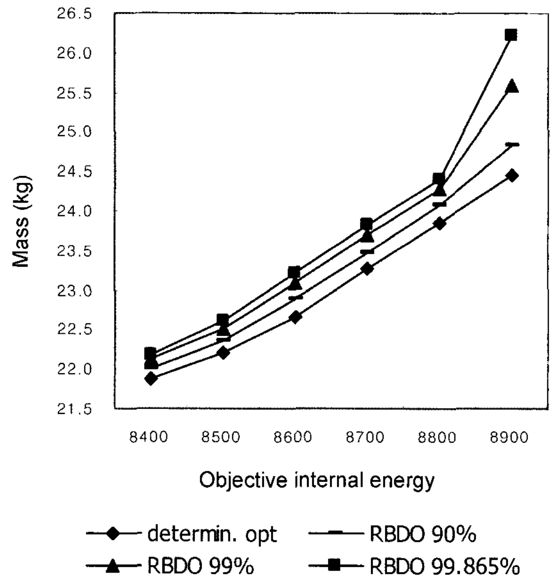


Figure 9. Weights of the optimal designs of the deterministic optimization and RBDO.

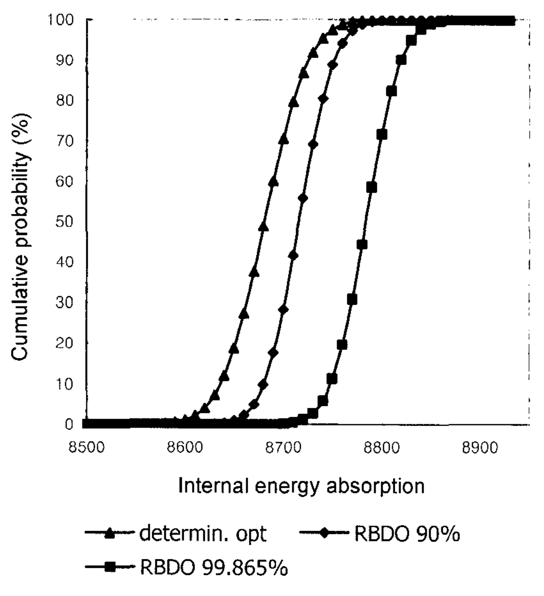


Figure 10. Cumulative probability distribution of the deterministic optimization and RBDO.

deterministic optimization was assumed to have the same deviation as that of RBDO.

It is noted that the probability of failure, that the design absorbs internal energy less than 8,700 J, is high in deterministic optimization result. And the probability of the failure decreases as the target reliability in RBDO increases. Consequently, RBDO gives a reliable optimal design even though it has some disadvantages in performance.

5. CONCLUSION

In this paper, the size optimization for the thicknesses of the engine room member was conducted to improve the capability of the crash energy absorption while keeping the weight of structure at the minimum. The response surface method was used for making a surrogate model of the vehicle crash behavior. The precision of the surrogate model affected the quality of the optimization result. Between the two methods used in this study, the moving least square method offered the better approximation than the least square method for the whole design domain. The optimal designs obtained by the moving least square method achieved the objective successfully. From the results, we were able to conclude that the response surface method is an efficient tool for resolving crashworthiness optimization problems if the appropriate regression method is adopted.

In addition to the deterministic optimization, the reliability based design optimization was executed in this study. The uncertainty of the thickness value was considered in RBDO. The result of the deterministic optimization showed better performance in reducing the vehicle weight. But the optimum from deterministic optimization showed a relatively higher probability of failure in achieving the objective energy absorption. As the target reliability level increased, the result of RBDO offered higher values in internal energy absorbing and showed lesser probability in failure. On the other hand, the high target reliability increased the weight of vehicle. Therefore, an appropriate target reliability level for each of the problem should be decided by the designer in RBDO optimization to ensure that an efficient and economical design is achieved.

REFERENCES

Arora, J. S. (1989). *Introduction to Optimum Design.* McGraw-Hill. New York.

Avalle, M., Chiandussi, G. and Belingrardi, G. (2002). Design optimization by response surface methodology: application to crashworthiness design of vehicle structures. *Struct. Multidisc. Optim.*, **26**, 325–332.

Barros Jr, P. A., Kirby, M. R. and Mavris, D. N. (2004). Impact of sampling technique selection on the creation of response surface models. *SAE Paper No.* 2004-01-3134.

Choi, K. K. and Youn, B. B. (2001). Hybrid analysis method for reliability-based design optimization. *27th ASME Design Automation Conf. DETC2001/DAC21044*, Pittsburgh, PA.

Choi, B. L., Choi, J. H. and Choi, D. H. (2005). Reliability-based design optimization of an automotive suspension system for enhancing kinematic and compliance characteristics. *Int. J. Automotive Technology* **6, 3,** 235–242.

Enevoldsen, I. and Sorensen, J. D. (1994). Reliability-based optimization in structural engineering. *Struct Safety*, **15**, 169–196.

Gonzalez, M., Chitoor, K., Kim, H. S. and Tyan, T. (2005). Testing and modeling of metalic multicorner columns in axial crush. *SAE Paper No.* 2005-01-353.

Gu, L., Yang, R. J. and Tyan, T. (2005). Structural optimization for crash pulse. *SAE Paper No.*2005-01-0748.

Kim, B. J., Kim, M. S. and Heo, S. J. (2005). Aluminum space frame B.I.W. optimization considering multidisciplinary design constraints. *Int. J. Automotive Technology* **6, 6,** 635–641.

Lancaster, P. and Salkauskas, K. (1986). *Curve and Surface Fitting; An Introduction.* Academic Press. London.

Madsen, H. O., Krenk, S. and Lind, N. C. (1986). *Methods of Structural Safety.* Prentice-Hall. New Jersey.

Myers, H. R. and Montgomery, D. C. (1995). *Response Surface Methodology.* John Wiley & Sons. New York.

Qi, C., Ma, Z. D., Kikuchi, N., Pierre, C., Wang, H. and Raju, B. (2005). Fundamental studies on crashworthiness design with uncertainties in the system, *SAE Paper No.* 2005-01-0613.

Redhe, M., Forsberg, J. and Jansson, T. (2002). Using the response surface methodology and the D-optimality criterion in crashworthiness related problems. *Struct. Multidisc. Optim.*, **24**, 185–194.

Riha, D. S., Hassan, J., Forrest, M. and Ding, K. (2004). Stochastic approach for vehicle crash models. *SAE Paper No.* 2004-01-0460.

Youn, B. D. and Choi, K. K. (2004). A new response surface methodology for reliability-based design optimization. *Computers & Structures,* **82**, 241–256.

Youn, B. D., Choi, K. K. and Park, Y. H. (2003). Hybrid analysis method for reliability-based design optimization. *J. Mech. Des., ASME* **125**, **2**, 221–232.

Youn, B. D., Choi, K. K., Yang, R.-J. and Gu, L. (2004). Reliability-based design optimization for crashworthiness of vehicle side impact. *Struct. Multidisc. Optim.,* **26**, 272–283.