Multi-Parameter Optimization Study on the Crashworthiness Design of a Vehicle by Using Global Sensitivity Analysis and Dynamic Meta-model

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Abstract: In a vehicle's concept design stage, there are usually a lot of design parameters need to be defined and optimized. For such a complex and non-linear system of a vehicle, multi-parameter optimization not only has a great computation, but also face the difficulty to obtain optimum solutions. This paper aimed at an optimization problem of a vehicle's crashworthiness with 20 design parameters, and presented a new method which uses global sensitivity analysis and dynamic meta-model. First, vehicle crash simulation model was constructed and design parameters were simplified by using global sensitivity analysis, then, the sensitive parameters were used to construct an initial meta-model. During the optimization solving process, the design domain and meta-model were updated continually until the accuracy of the solutions met the requirement of the convergence criteria. Final results showed that the presented method in this paper could not only successfully solve the multi-parameter optimization problem, but also significantly reduce the computation time and cost.

Keywords: Multi-parameter Optimization, Vehicle Crashworthiness, Concept Design, Global Sensitivity Analysis, Dynamic Meta-model.

1. Introduction

Generally, to develop a totally new car, it has to go through three stages: concept design, detailed design and engineering modifying, among which concept design mainly involves in the defining of overall performance, overall parameters and structure forms, etc., which then become the basis for later design. During the whole process of the car development, concept design is so important because in this stage, the design space is very big and the defined results have great effect on the development[1]. According to relative statistics, when concept design finishes, about 70% of the total cost for the car development can be estimated out[2]. Therefore, it can be concluded that the success of a new car's development relies much on the concept design.

Concept design of a car involves in many aspects. In this paper, it is only going to discuss about the concept design of crashworthiness, i.e., the optimum matching design of body structure and occupant restraint system. Traditional way was that of defining body structure first and then occupant restraint system was matched by using computer simulation and optimization method. For example, references [3,4,5,6] introduced the similar work of optimization matching design of occupant restraint system on the basis of defined body frame structure. This kind of design usually involves few design parameters and can be classified as local optimization problem. Although it is simple, it is hard to make it optimum of the overall cost and overall performance at the same time. If the performance of the body structure is not so good, then great challenge will be there for the matching design of occupant restraint system, accompanied by rising cost. An improved method is to design body structure and occupant restraint system concurrently, however, this will make the design become more complex because the parameter numbers increase a lot, thus the computation cost grows fast, and optimization work becomes very difficult[7]. Thus, it is necessary for researchers to find a way to solve the problem of optimization for high

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nonlinear system with multi-parameters.

In this paper, in order to conduct concept design for the match of a new car's body structure and occupant restraint system, a simplified simulation model is established with 20 design parameters defined. Then, global sensitivity analysis method based on variance is used to find out and select important design parameters, which are used to establish meta-model. Finally, a new method is proposed to update meta-model and global optimum solution is obtained after 5 iterations. The method presented in this paper can be as a reference for solving the problem of the optimization design of high nonlinear system with multi-parameters.

2. Methodology

2.1 Establishment of simplified concept model for crash analysis

In the stage of a car's crashworthiness concept design, what is needed to consider is the match design of the performances of body structure and occupant restraint system. The body structure's performance can be described by an Equivalent Dual-Trapezium Wave(EDTW) as the broken line shown in Figure 1. EDTW is a simple curve, which is not only capable of replacing the complex curve(as the full line shown in Figure 1), but also reflects the important information of the crashworthiness, such as the first step acceleration a_1, the second step acceleration a_2, and also the important impact moments t_c, t_e, etc.

For EDTW In Figure 1, only the wave shape is assumed, while the parameters a_1, a_2, t_c, t_e, etc. are all unknown and need to be defined within a given design space.

For the occupant restraint system, Madymo software which is specialized for dynamic analysis of multi-rigid body is used to establish a simulation model which includes window shield, steering system, seatbelt, airbag, seat, floor and Hybrid III 50% male dummy, as shown in Figure 2. All the parameters for occupant restraint system design are included in this model.

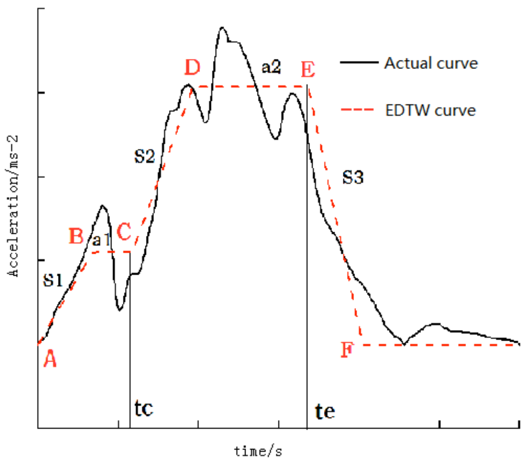

Figure 1: EDTW used in the concept design of crashworthiness

Figure 2: Simulation model for occupant restraint system

By now, a complex system is established. EDTW in Figure 1 is an input for the simulation model in Figure 2 when impact simulation begins. The goal of the concept design is to define all the parameters, which are a_1, a_2, slope s_1, s_2, s_3 and moment t_c included in Figure 1 and the force limit of seatbelt force limiter Fx, seatbelt preload l, preload time of the seatbelt pre-loader Ty, belt stiffness δ, height of the seatbelt D ring, the ignition time of the airbag t_i, vent hole area scale s, airbag volume v, air inflation portion p, coefficient of air permeability c, steering wheel angle W_A, seat position S_P, seat back angle S_A and knee bolster stiffness k, etc. which are included in Figure 2. The initial values and varying spaces for all the parameters are assumed as shown in Table 1.

Table 1: All the design parameters, initial values and varying spaces

Design parameters/unit	Initial values	Varying spaces	Design parameters/unit	Initial values	Varying spaces
a_1/ms^{-2}	108	[90, 150]	δ	16%	[10%,20%]
a_2/ms^{-2}	304	[240,350]	v/L	30	[26,34]
S_1/ms^{-3}	7900	[6300,9400]	s	1.0	[0.8,1.2]
S_2/ms^{-3}	12900	[10300,15500]	t_i/ms	25	[20,30]
S_3/ ms^{-3}	-18	[-20,-16]	p	1.0	[0.8,1.2]
t_c/ms	23	[20,26]	c	0.7	[0.6,0.8]
F_x/N	4000	[3000,5000]	K	1.0	[0.8,1.2]
l/mm	35	[30,80]	S_P/mm	258	[248,268]
H/m	1	[0.9,1.1]	S_A/deg	17	[10,25]
T_y/ms	15	[10,20]	W_A/deg	29	[27,31]

2.2 Optimization Model for the System Design

In order to conduct the concept design, an optimization model needs to be established. The objective of the optimization is to reduce the occupant injury by using computer simulation method. The occupant injury evaluation involves in head, chest and legs, and the corresponding index are Head Injury Criterion (*HIC*), chest acceleration within 3ms (C_{3ms}), chest depression(D), and leg axial force(F) respectively, which should not exceed the respective limits. In this paper, a Weighted Injury Criterion[8](*WIC*) which combines *HIC*, C_{3ms}, D and F is used as described by Eq.(1):

$$WIC = 0.6(\frac{HIC}{1000}) + 0.35(\frac{C_{3ms}}{60} + \frac{D}{75}) / 2 + 0.05(\frac{F_{FL}+F_{FR}}{20}) \tag{1}$$

Where, F_{FL} and F_{FR} are the axial forces of left leg and right leg respectively.

Thus, the mathematical optimization model is established as follows:

Variables: a_1, a_2, S_1, S_2, S_3, t_c, F_x, l, H, T_y, δ, v, s, t_i, p, c, k, S_P, S_A, W_A

Min *WIC*

S.t. $HIC \le 1000$, $C_{3ms} \le 60$g, $D \le 75$mm, $F_{FL} \le 10$KN, $F_{FR} \le 10$KN.

How to resolve the above optimization problem? Traditional mathematical optimization methods are obviously unable to do so because of large computation involving in iterations. With the development of numerical meta-model method in recent years, optimization efficiency has been improved a lot. The most representative meta-models are Response Surface Model (RSM), Kriging model and Radial Basis Function (RBF) model. However, researches showed that each kind of meta-model has its adaptability. For example, RSM is easy to construct and has high efficiency of response prediction, but is unsuitable for high nonlinear system; Kriging model is suitable for high nonlinear system as long as the parameters' number is within 8; RBF model has moderate accuracy and efficiency, and its local accuracy is hard to achieve when used for high nonlinear system with multi-parameters[9]. Therefore, if parameters' number can be reduced for high nonlinear system, then it is more convenient to obtain the solution. Reference [10] presented a method named global sensitivity analysis based on variance which can be used to find out sensitive parameters, so those insensitive parameters can be removed and the total parameters number reduced.

2.3 Theory of Global Sensitivity Analysis Based on Variance

It is assumed that there is a system expressed as Eq.(2):

$$\mathrm{Y}=f(X) \tag{2}$$

$$X=(X_{1,}X_{2,}\ldots X_{k,})$$

Where X_i is independent with each other and uniformly distributed within [0,1].

By using Monte Carlo sampling method, two matrices A, B are generated as follows:

$$\boldsymbol{A}=\begin{bmatrix} x_{11} & \cdots & x_{1i} & \cdots & x_{1k} \\ x_{21} & \cdots & x_{1i} & \cdots & x_{2k} \\ .. & \cdots & \cdots & \cdots & \cdots \\ x_{n1} & \cdots & x_{1i} & \cdots & x_{nk} \end{bmatrix}, \boldsymbol{B}=\begin{bmatrix} x'_{11} & \cdots & x'_{1\mathrm{i}} & \cdots & x'_{1\mathrm{k}} \\ x'_{21} & \cdots & x'_{2\mathrm{i}} & \cdots & x'_{2\mathrm{k}} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x'_{\mathrm{n}1} & \cdots & x'_{\mathrm{ni}} & \cdots & x'_{\mathrm{nk}} \end{bmatrix}$$

Where k is the design parameters number and n is the sampling number.

If the i column of matrix B is replaced by the i column of matrix A, and the i column of matrix A is replaced by the i column of matrix B, then another two matrices C_i and C_{-i} are generated:

$$\boldsymbol{C}_i=\begin{bmatrix} x_{11} & \cdots & x'_{1\mathrm{i}} & \cdots & x_{1k} \\ x_{21} & \cdots & x'_{2\mathrm{i}} & \cdots & x_{2k} \\ .. & \cdots & \cdots & \cdots & \cdots \\ x_{n1} & \cdots & x'_{\mathrm{ni}} & \cdots & x_{nk} \end{bmatrix}, \boldsymbol{C}_{-i}=\begin{bmatrix} x'_{11} & \cdots & x_{1i} & \cdots & x'_{1\mathrm{k}} \\ x'_{21} & \cdots & x_{2i} & \cdots & x'_{2\mathrm{k}} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x'_{\mathrm{n}1} & \cdots & x_{ni} & \cdots & x'_{\mathrm{nk}} \end{bmatrix}$$

By substituting above matrices into Eq.(2), the corresponding outputs can be obtained. It is assumed that $\boldsymbol{y_A}$, $\boldsymbol{y_B}$ and $\boldsymbol{y_C}$ are the output vectors corresponding to the input matrices $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{C}$, then the estimated variance is calculated by Eq.(3):

$$\hat{V}(Y)=\frac{1}{n}y_A^T(y_A-y_B) \tag{3}$$

Where $\hat{V}(Y)$ is the total variance.

At the same time, followings are defined as Eq.(4), Eq.(5) and Eq.(6):

$$\hat{f}_0^2=\frac{1}{n}y_A^Ty_B \tag{4}$$

$$\hat{U}_i=\frac{1}{n}y_A^Ty_{C_i} \tag{5}$$

$$\hat{U}_{-i}=\frac{1}{n}y_A^Ty_{C_{-i}} \tag{6}$$

Then for the input parameter x_i, the main effect index $\overline{S}_{x_i}$ is estimated by Eq.(7):

$$\bar{S}_{x_i} = \frac{\hat{U}_i - \hat{f}_0^2}{\hat{V}(Y)} \tag{7}$$

And the whole effect index $\bar{S}_{x_i}^T$ is estimated by Eq.(8):

$$\bar{S}_{x_i}^T = \frac{\hat{V}(Y) - (\hat{U}_{-i} - \hat{f}_0^2)}{\hat{V}(Y)} \tag{8}$$

The main effect index reflects the influence of single parameter on the system response, while the whole effect index not only reflects the single parameter's influence on the system response, but also reflects the parameters' interaction influence.

As to the system studied in this paper, by using the above method, the estimated main effect index and whole effect index of each parameter are calculated, and the results are shown in Table 2.

Table 2: Parameters, main effect and whole effect index

parameters	a_1	a_2	S_1	S_2	S_3	t_c	F_x	l	H	T_y
Main effect	-0.0018	0.4371	-0.0006	0.0034	0.0193	0.0171	0.0693	0.0276	0.0081	0.003
Order	18	1	17	13	7	8	4	5	10	12
Whole effect	0.0274	0.4630	0.0465	0.0434	0.0268	0.0372	0.1013	0.0395	0.0133	0.008
Order	11	1	6	7	12	9	4	8	14	18

Table 2: (Continues)

parameters	δ	v	s	t_i	p	c	K	S_P	S_A	W_A
Main effect	-0.0200	0.0259	0.1606	-0.0018	0.1038	-0.4E-4	-0.0003	0.0056	0.0159	0.001
Order	20	6	2	19	3	15	16	11	9	14
Whole effect	0.0213	0.0707	0.2467	0.0274	0.1199	0.1E-4	0.0049	0.0090	0.0133	0.009
Order	13	5	2	10	3	20	19	17	15	16

According to the results in Table 2, 11 parameters with higher index values are selected. Although the parameters number is reduced from 20 to 11, it is still hard to construct a single meta-model which has expected local and overall accuracy. Thus, during the iteration process, meta-model needs to be updated again and again in order to be more and more accurate till the solution is obtained.

2.4 Technique of Dynamic Meta-model

Meta-model continuously changes, then dynamic meta-model emerges. i.e., during the process of each iteration, design space reduces continually, and a new meta-model is constructed to replace the old one. The theory and algorithm for constructing dynamic meta-model are introduced below.

(1) First step, Hypercube Latin method is used to sample within the given initial design space, thus the whole design space can be described by a few samples, correspondingly, the system responses are calculated and thus initial meta-model can be established;

(2) Second step, the initial meta-model is solved by using multi-island genetic algorithm, and the first

solution is obtained;

(3) Third step, updating design space. For the kth times iteration, a design space is defined by Eq.(9) based on the solution $x_{k-1}'^{\,*}$ of the k-1th times iteration:

$$(S_k^{L'}, S_k^{U'}) = (x_{k-1}'^{\,*} - \frac{1}{10}L_{k-1}, \quad x_{k-1}'^{\,*} + \frac{1}{10}L_{k-1}) \tag{9}$$

Where, $S_k^{L'}$ and $S_k^{U'}$ are the lower and upper limit of the design space respectively for the kth times iteration, and L_{k-1} is the design space size for the k-1th times iteration;

(4) Fourth step, by using global sensitivity analysis during the k-1th times iteration, another solution $x_{k-1}''^{\,*}$ is obtained , thus for the kth times iteration, another design space is defined by Eq.(10) based on $x_{k-1}''^{\,*}$:

$$(S_k^{L''}, S_k^{U''}) = (x_{k-1}''^{\,*} - \frac{1}{10}L_{k-1}, \quad x_{k-1}''^{\,*} + \frac{1}{10}L_{k-1}) \tag{10}$$

(5) Fifth step, the design space for the kth times iteration is updated by considering the above two defined spaces and also the initial design space, which can be expressed by Eq.(11):

$$(S_k^{L}, S_k^{U}) = (S_k^{L'}, S_k^{U'}) \quad (S_k^{L''}, S_k^{U''}) \quad S \tag{11}$$

(6) Sixth step, convergence criterion. New meta-model is constructed based on new samples sampled from the updated design space and iteration calculation is going on until solution is obtained. If the error between the two solutions of kth and k-1th time iteration is less than ξ(assigned value of 0.5%), also at the same time, the solutions between meta-model and simulation model is less than 5%, then the global optimization ends, otherwise, the iteration continues until the convergence criterion is satisfied.

2.5 Optimization results

By 5 times iteration, the results converged. All the parameter's initial values and the corresponding optimized results are shown in Table 3. Compared with initial injury values, *WIC* is reduced by 36.5% after optimization.

Table 3: Parameters, initial values and optimized results

Parameters (input and output)	Initial values	Optimized results	Parameters (input and output)	Initial values	Optimized results
a_1/ms^{-2}	108	112	s	1.0	1.01
a_2/ms^{-2}	304	243	p	1	1.08
S_1/ms^{-3}	7900	9368	t_i/ms	25	24.6
S_2/ms^{-3}	12900	13771	*HIC*	754	400
t_c/ms	23	25	C_{3ms}/g	56.3	43.6
F_x/N	4000	4458	*D*/mm	37	33
l/mm	35	66	*WIC*	0.717	0.455
H/m	1	0.973			

3. Conclusion

This paper studied the optimization design problem for a high nonlinear system with multi-parameters during a new car's crashworthiness concept design stage. A simplified concept simulation model was established first and then the methods of Global Sensitivity Analysis and dynamic meta-model were used to do research and optimization. The productive work of the research was that the number of design parameters was reduced effectively and system model was simplified, which in a great degree made the optimization computation cost reduced and the global optimum solution obtained. The research work done in this paper can be a good reference for other similar optimization problems in modern engineering.

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