Advanced Body in White Architecture Optimization

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Abstract: During the BIW concept developing phase, some key design variables, such as rails and pillars width and position, shell thickness, etc, and multi-attribute responses from safety, NVH, and durability are considered to explore the design space. Isight DOE design drive is used to assess the impact of the variables on the objectives, and this helps the engineer to better understand the design space and give design recommendation. Approximations component is used sequentially to create fast-running surrogate models to replace the real CAE simulations. Finally, the Optimization tool is used to perform a trade-off study, and this helps engineer to know what is the minimum cost for the design to meet all design targets, or when the BIW weight is fixed, what is the potential maximum design performance.

Keywords: BIW(Body in White) , design variable, multi-objectives, DOE, Approximation, Optimization, Trade-off

Introduction

Low cost and high quality is now a new question for every automotive center to meet the fast growing market's requirement. For BIW development, we need minimize BIW mass based on the performance requirements. This paper explains an acceptable process of the advanced BIW architecture optimization in the early stage of vehicle development.

1. Project definition and DOE

1.1 Loadcase and design variables

For a new architecture development, we should analysis the feasibility of the representative loadcases in the early stage of the development, and make a clear loadcase list for the optimization process. In this BIW architecture optimization, we defined five loadcases: BIW static stiffness, mode, 100% RGB, 40% ODB and Side Impact. Then, the BIW architecture design variables are selected from the rail position, rail angle, section size, panel thickness and material based the engineering experience and the design direction of this vehicle. The design variables' range is restricted by the package protection and benchmark compare. At last we defined the output responses according to the loadcases' evaluation factors. Sum up this optimization process, we have 58 design variables and 37 responses.

1.2 Parametrical BIW CAD model

According to the package key points and design variables inputs, we created a parametrical BIW CAD model by SFE-Concept. Use this model, we can automatically change the BIW structural parameters as the engineering requirements input and export FE meshes and spot welds in formats compatible with several finite element solvers such as MSC.Nastran, LSDyna, Abaqus, PAM-Crash etc. After we integrated this model into Isight loop, we can use this model to do multidisciplinary optimization. The parametrical BIW CAD model is shown in Figure 1.

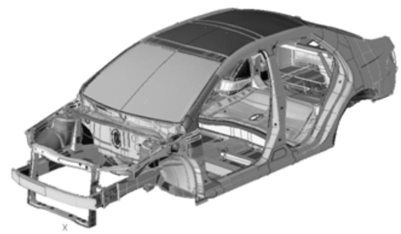


Figure 1. Parametrical BIW CAD model

1.3 Design of Experiment (DOE)

DOE is the base of the total optimization process. The standard approach for DOE is as follows:

a. Define DOE matrix

b. Generate designs according to DOE matrix

c. Evaluate designs in parallel

d. Extract responses from simulation runs into a database

e. Perform statistical analysis on responses from DOE

The amount of the samples lies on the design variables scale. From the engineering aspect, we must minimize the samples and establish a high accurate response surface. The response surface's accuracy is highly influenced by the DOE method we selected. There are many DOE methods provided in Isight, and we recommend the Optimal Latin Hypercube and Orthogonal Array methods. On the other hand, due to the non linear complexity between response and variables, the minimum samples for some special responses are different from the DOE matrix we defined. In our BIW optimization, we analyzed all the variables and responses and adjusted the initial DOE matrix. After that, we build a DOE loop in the Isight environment and export all FE model samples. Once we finished the computer experiments in parallel, we achieved all responses values by Isight loop. Some design variables matrix is shown in Table 1.

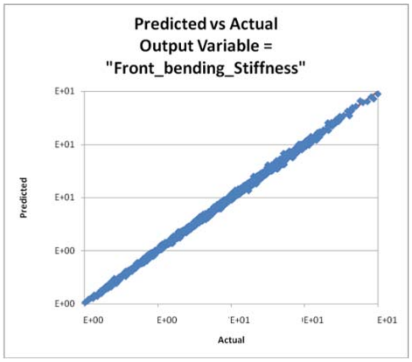
Table 1 DOE Matrix

Run	Rail_A_Width	Rail_B_Height	Rail_C_Height_at_P1	Rail_D_Position	..	Part_X_Gauge
1	42.625	55.4	105.2	109.6	..	1.0
:	:	:	:	:	:	:
500	66.25	68.7	97.325	70.85	..	2.4
:	:	:	:	:	:	:
m	60.625	83.9	99.95	104.95	..	0.8

2. Approximation and ANOVA

2.1 Approximation

Approximation is one of the key factors of the optimization's accuracy. Usually, the techniques we applied are: Polynomial model, Radial Basis Function and Kriging model. We need use these methods properly according to the BIW variables situation. After the Approximation model is constructed, we did the cross validation and random samples check in order to confirm the model's accuracy. The validation and samples result shows that our approximation model can meet the advanced development's requirement. Figure 2 - Figure 5 shows the cross-validation result of the Front End Bending Stiffness. And table 2 shows two random samples error check results of some responses.



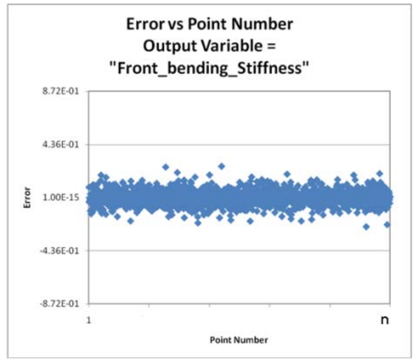
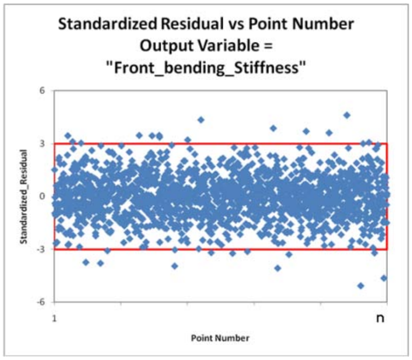


Figure 2

Figure 3



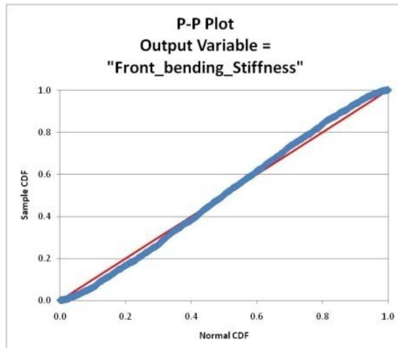


Figure 4

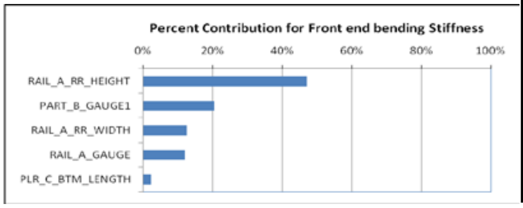
Figure 5

Table 2 random samples error check

Response / No.	1st Torsion Mode	Global Bending Stiffness	Mass	100%RGB Effect Acc.	100%RGB Effect Crush
1	-0.03%	0.23%	0.90%	-5.19%	4.57%
2	0.18%	0.15%	-0.03%	0.34%	-3.86%

2.2 ANOVA

ANOVA analysis is widely used in engineering area, also in automotive development. After we created the approximation model, we can find the relationship between variables and responses, and the contribution to the responses for each variable by ANOVA. Thus we can make correct estimate and find the key point for a specific performance. From Main Effect chart we can get the relationship of each variable to the objectives "peak force" and "head-Trim distance" , also we can analyze the potential trend from current design point. Figure 6 to Figure 7 show the percent contribution to Front End Bending Stiffness and Effective Acceleration of 100%RGB. Figure 8 and 9 show the main effect charts of these two responses.



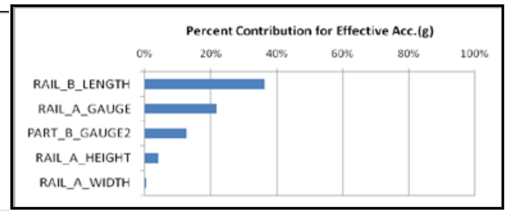
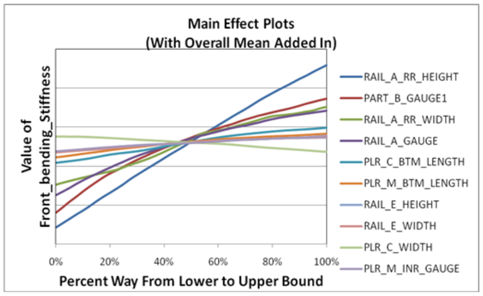


Figure 6. Front end bending contribution Figure 7. 100%RGB effective Acc. contribution



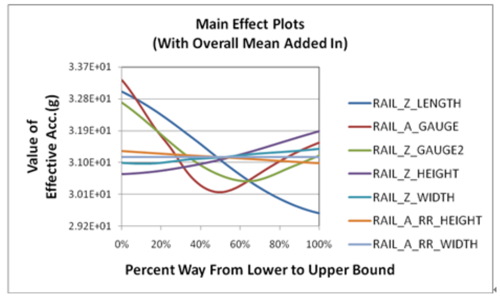


Figure 8. Front end bending main effect Figure 9. 100%RGB effective main effect

Based on Fig.6, it can be seen easily that RAIL_A_RR_HEIGHT contributes with nearly 50% or the total RAIL_A area affects more than 70% to the Front end bending stiffness. From Fig.7, it can be seen that RAIL_B_LENGTH contributes more than 30% to the 100%RGB Effective Acc, and the total RAIL_A and RAIL_B area affects more than 90%, i.e. the definition of RAIL_A and RAIL_B will be the crucial aspect for the Effective Acc.

In Figure 8 , it can be seen that most parts analyzed have a linear response for any of the objective, this due to the linear analysis of stiffness simulation. In Fig. 9 can be seen that RAIL_A_GAUGE and RAIL_Z_GAUGE2 have a nonlinear behavior. For linear response, the accuracy of approximation model is higher than nonlinear response, and this is well validated by the stiffness sample's accuracy is higher than the Effective Acc.

3. Optimization

3.1 Process definition

In general, a design optimization problem formulation can be expressed as

$$\begin{aligned} &\max \quad Performance \\ &\text{s.t.} \quad lb_i \le x_i \le ub_i \qquad i = \overline{1,n} \end{aligned} \tag{1}$$

where xi is the i-th design variable, lbi and ubi are the lower and upper bounds for the variable xi, respectively, and n is the number of design variables. ‘Performance’ is typically a set of simulation responses which need to be balanced in a final design. If some of the responses have defined target values then they can be included in the problem formulation as constraints. Then eq. (1) can be written as

$$\begin{aligned} &\max \quad Performance \\ &\text{s.t.} \quad lb_i \le x_i \le ub_i \qquad i = \overline{1,n} \\ &\qquad LB_j \le g_j(x) \le UB_j \qquad j = \overline{1,m} \end{aligned} \tag{2}$$

where gj(x) is the j-th constraint, LBj and UBj are the lower and upper bounds for the response value defined with the constraint gj(x), respectively, and m is the number of constrained responses. The optimization problem described in eq. (1) is considered unconstrained, while the optimization problem described in eq. (2) is considered constrained.

The ultimate target for BIW optimization is minimize mass and meet performances requirement; but there are some special conditions such as we need keep mass and maximize performance. Hence, we should consider different optimization process for different problems. In order to deep dive the structural potential for each loadcase, we defined 9 optimization processes which include 2 mode Opt. processes, 2 stiffness Opt. processes, 3 safety Opt. processes and 2 combined processes. Table 3 shows the detailed optimization problems list.

Table 3 optimization problems definition

Process No / Performance	1	2	3	4	5	6	7	8	9
[Mode]	≥[A]	[Max]	-	-	-	-	-	≥[A]	[Max]
[Stiffness]	-	-	≥[C]	[Max]	-	-	-	≥[C]	[Max]
[Safety1]	-	-	-	-	[Min]	[Min]	≤[E]	≤[E]	[Min]
[Safety 2]	-	-	-	-	[Max]	[Max]	≥[F]	≥[F]	[Max]
[Safety3]	-	-	-	-	≤[D]	[Min]	≤[G]	≤[G]	[Min]
Mass	Min	≤B	Min	≤B	Min	Min	Min	Min	≤B

3.2 Optimization runs

For Multi-Disciplinary Optimization, Adaptive Simulated Annealing (ASA), Genetic Algorithm (GA) are widely used. There are several SA and GA optimization methods in Isight, each method has its specialty to meet different optimization cases' requirement. The final result is not the same for one optimization process with different methods, even two Opt. runs with the same method. The ASA, NCGA and NSGA-II in Isight are all multi-objective exploratory techniques. ASA is based on the disciplinary which combined the objectives with different weights into one object, so in essence, it is still single object method. This kind of multi-objective methods can still satisfy our requirement if only we defined the weights properly. But if we want to get a perfect optimization result, we must strictly adjust the weights according to the engineering requirement. NCGA, NSGA-2 and AMGA are pure multi-objective optimizers that optimize for the entire pareto front and a weighted objective is not necessary.

Design variables can be continuous or discrete. Continuous variables are the most common. Some examples include: dimensions of structural members, relative position of structural members, part thickness, weld pitch, etc. Typical discrete variables are material type, different sub-system options (e.g. cradle options A, B and C), presence or absence of a certain part or a sub-system (e.g. if a weld is present at the specified location the value of the variable is 1, otherwise is zero), etc. The type of design variables is very important when selecting an optimization technique as some algorithms cannot be used in mixed and discrete domains. So we applied different techniques for different optimization processes. Table 4. shows the final result of 100%RGB optimization process.

Table 4 Part of 100%RGB result

Design Variables	Difference	Response Variable	Difference
CRASHBOX_HEIGHT	-30.09%	Effective Acc.	-16.66%
CRASHBOX_WIDTH	23.76%	Efficiency	+11.83%
CRASHBOX_LENGTH	42.57%	TOTAL MASS	-0.03%
FRTRAIL_RR_HEIGHT	-1.78%	Intr. @ A Pillar_R1	+4.61%
:	:	:	:
FRTRAIL_GAUGE	10.00%	Dash Intr. @ toepan_R4	+7.32%

After we have got the optimization result, we need simulation runs to correlate the result. For some results which is not reliable, we need add the result points to the database and create a new approximation model. In this BIW case, the final result is obtained by repeated simulation runs. Some errors of predicted values are showed in table 5.

Table 5 Part of 100%RGB optimization results error

	Zero Crossing Time	Dynamic Crush	Effective Crush	Effective Acc.
Error	-2.47%	-0.14%	-3.86%	0.34%

3.3 Result analysis

Isight provides a cross-functional support on the optimization result analysis. By Trade-Off Analysis, we get the relationship of two responses in current BIW design. This is very helpful for us to estimate the influence from one response to another. Figure 10 & 11 shows the trade off results between mass and Dash Intrusion and Effective Acc. The black points are unacceptable designs, and the light grey points are the designs which can only be accepted by the responses shows in the figure, the dark grey points are the acceptable designs which can meet all responses' requirements. From Fig.11, if mass meets level A, the Effective Acc. can meet level B; i.e. in the current design space, if we want to meet the mass target A, we cannot achieve the Effective Acc. performance below level B. The curve shows us a balance guidance between mass and Effective Acc. in the figure.

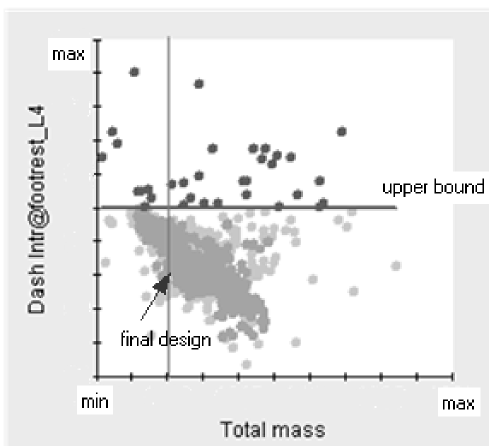


Figure 10 Dash Intrusion vs mass Trade-Off

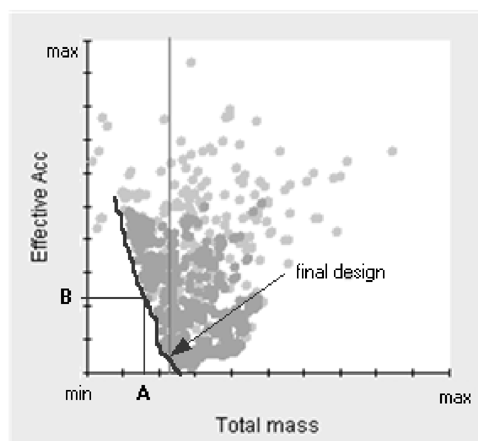


Figure 11 Effective Acc. vs mass Trade-Off

4. Conclusion

The use of BIW Multi objectives optimization had presented us several achievements: An acceptable method to predict the performances in the BIW architecture developing stage; The structural sensitivity for a specific performance target; A best BIW architecture frame based on a specific performance; The relationship of two responses in current BIW design space. After deep dived the manufacturing feasibility and balanced the package and styling protection, we got a available BIW architecture frame proposal of this vehicle.

Reference

1. Problem Formulation and Optimization Method Selection in Multi-Disciplinary Design Optimization.GM VSAS Analysis Guideline, Vesna Savic, Mar-19, 2008

2. A Taxonomy of Global Optimization Method Based on Response Surfaces. Donald R. Jones, GM, Journal of Global Optimization 21: 345-383, 2001
3. Reliable Multidisciplinary Optimization With Response Surfaces. Don Jones, Simon Xu, GM, 2007 GM Global CAE Conference, Sep, 2007
4. An Efficien Algorithm for Constructing Optimal Design of Computer Experiments. Ruichen Jin, Wei Chen, Integrated Design Automation Laboratory Northwestern University, 2003
5. Analysis & Optimization of a vehicle structure, using Kriging metamodels. Mauricio E. Frias Alvarez, GM, 2007 GM Global CAE conference, Sep, 2007
6. EFFICIENT PARETO FRONTIER EXPLORATION USING SURROGATE APPROXIMATIONS. Benjamin Wilson, etc, AIAA-2000-4895
7. A Fast and Elitist Multiobjective Genetic Algorithm:NSGA-II. Kalyanmoy Deb, Associate Member, IEEE, Amrit Pratap, Sameer Agarwal, and T. Meyarivan, IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION, VOL. 6, NO. 2, Apr, 2002
8. A Comparison of Approximation Modeling Techniques: Polynomial Versus Interpolating Models Anthony A. Giunta,National Research Council/NASA Langley Research Center Postdoctoral Research Associate, MAD Center Advisory Board Meeting, Nov 14−15, 1997
9. Hedayat, A.S., Sloane, N.J.A., Stufken, J., Orthogonal Arrays: Theory and Applications, Springer, 1999
10. Ingber, L., Adaptive Simulated Annealing (ASA): Lessons Learned, Journal of Control and Cybernetics, 1996, v. 25, No. 1, pp. 33-54
11. Global Guidelines for Creation of FE Entities in SFE CONCEPT Models. Vesna Savic, GM VSAS Analysis Guideline, May-08, 2008
12. Isight-FD help Documentation