DEVELOPMENT OF A DOE/OPTIMIZATION CAE METHOD TO SIMULTANEOUSLY IMPROVE SIDE IMPACT OCCUPANT RESTRAINT SYSTEM PERFORMANCE FOR MULTIPLE TEST MODES

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ABSTRACT

The automotive industry today faces the challenge of developing a single side impact occupant restraint system to meet performance requirements for multiple crashworthiness test modes. The side air bag, door liner, and vehicle side body structure are key systems that affect the injury criteria of the occupant. This paper discusses how DOE/optimization methods are used to quickly develop a specification for the side air bag and door liner that meets occupant injury criteria for three different side impact test modes. The work detailed in this paper focuses on occupant protection assessment based on three different CAE side impact sled models using ES2-re, DOT-SID and SID-2s, dummy models to evaluate the new FMVSS 214, SINCAP and SICE test modes.

Ten design variables were selected from air bag and door liner parameters which include mass flow rates, vent areas, two variables that define the location of the bag, and material/thickness of the door liner. Occupant injury parameters such as rib deflections/accelerations, pelvis accelerations/forces, and abdomen forces were selected as the responses. As the first step, a latin hypercube DOE method was used to evaluate sensitivity of the design variables to occupant injury parameters. Based on the DOE dominant design variables, optimization criteria and methods were established for the next step. Key injury criteria for each test mode were selected as the constraints. A self adaptive evolution (SAE) global optimization method was used to carry out automated simultaneous simulations. Based on the optimization results eleven feasible design specifications were found. Out of these candidates the optimum design was selected for further evaluation.

INTRODUCTION

Government and insurance institutions have introduced many safety standards that auto manufacturers should comply with to reduce the risk of serious and fatal injury to occupants in side impact crashes. To achieve a desired crashworthiness the auto industry focuses on developing better side body structures and efficient occupant restraint systems.

Typically the vehicle is subjected to multiple side impact test modes to verify that it meets the required standards. The traditional approach is to tune the restraint system to each test mode separately. This is a very laborious process as a restraint system which is good for one test mode may not work for another. This may induces higher costs and large lead times to find a restraint system that is good for all test modes. Still the engineer may not find the optimum system.

Today the use of occupant simulation is an integral part of restraint system development process. This study introduces an occupant simulation based methodology to find an optimum restraint system in a multi test mode scenario.

This methodology employs design of experiments (DOE) and numerical optimization techniques. Design variables that are most sensitive to the responses and optimization technique were found based on the DOE. A latin hypercube sampling method was selected for the DOE. This is because the user can specify the number of experiments and it ensures the ensemble of random numbers as a good representative of the real variability.

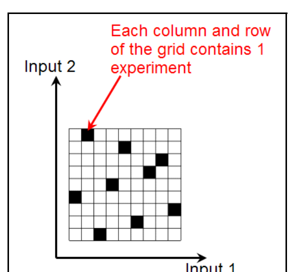


Figure 1. Latin Hypercube Technique

As shown in Figure 1 the Latin hypercube generates random experiments which are more uniform across the design space.

The numerical optimization method employed was self adaptive evolution. This is a global optimization method in which results are not depended on the starting point. Also iterations are calculated in parallel and tend to converge to a global optimum.

This paper also discusses the application of the response surface method (RSM). A response surface is a simplified multi-dimensional surface fit to what is usually a more complex function. Response surface functions were developed by fitting taylor polynomial models through the DOE results. This was done primarily to evaluate fidelity of such functions for future work and also to quickly find design trade offs.

SCOPE OF THE PROJECT

Moving deformable barrier impacts are key to evaluate side restraint system. Therefore side sled models derived from new FMVSS 214, SINCAP and SICE test modes were used in this study. Air bag and door liner spec were varied to optimize the restraint system. Occupant injury criteria for each test mode were selected as the responses.

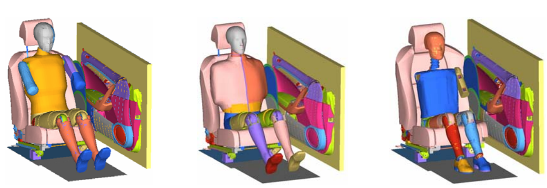
General Outline of the Project

- Process Integration and Automation: Creation of a work flow that automatically generates executes and extracts results for multiple design iterations.

- Design of Experiments (DOE): Evaluate sensitivity of air bag and door liner design variables to occupant injury criteria.

- Optimization: Finding the optimal characteristics for airbag and door liner that meets all injury criteria targets.

- Response surface model generation based on the design of experiments to evaluate fidelity of such functions.



New FMVSS 214 with ES2-re | SINCAP with DOT-SID | SICE with SID-2S

Figure 2. Sled simulation models.

LS-DYNA dynamic code was used for sled test simulations.

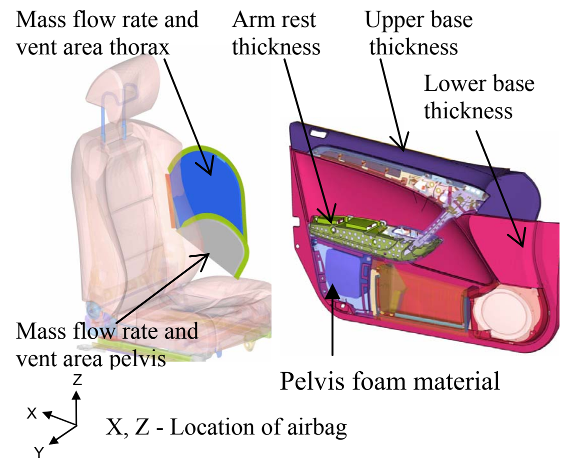


Figure 3. Design Variables.

OPTIMUS process automation software was used to integrate all 3 sled models into a single work flow which would make all simulations run in batch mode. This work flow automatically generates, executes input simulation files, and extracts results for multiple design iterations. This automation allows the user to evaluate multiple designs with little or no manual intervention.

DESIGN OF EXPERIMENTS

The number of experiments required in order to make valid conclusions is directly proportional to the number of design variables in the process. Therefore it is important to get the correct composition of design variables (some times referred as factors) that defines the problem which generally comes with experience. How much resources are available is a another important factor that effects the number of experiments to be conducted. Figure 4 shows the 10 design variables selected and their ranges normalized with respect to the upper bound.

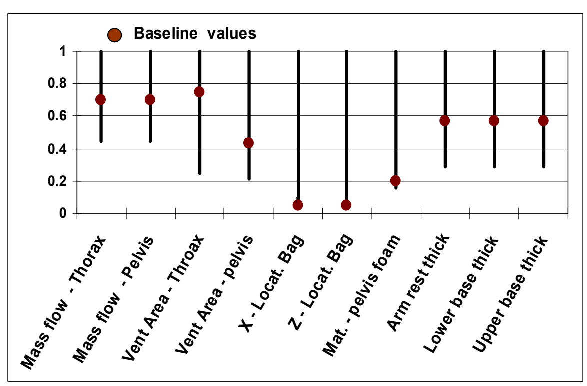


Figure 4. Air bag and door liner design variables.

For responses, rib deflections/acceleration, pelvis accelerations/forces, and abdomen forces were measured. Injury criteria targets are based on the allowable response values dictated by each test mode. Figures 5,6,7 show baseline responses, normalized with respect to allowable levels.

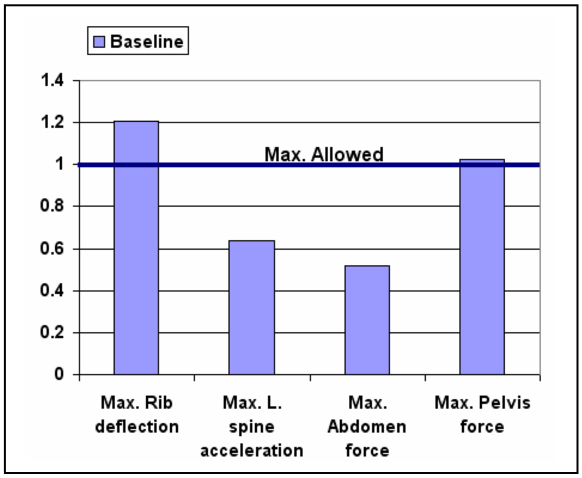


Figure 5. New 214 - Baseline injury responses

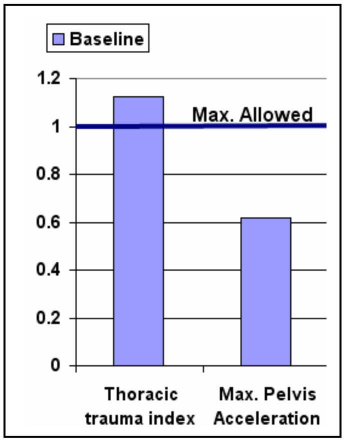


Figure 6. SINCAP - Baseline injury responses

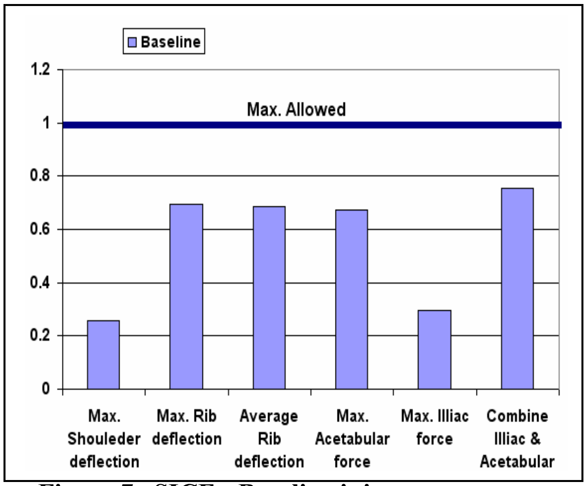


Figure 7. SICE - Baseline injury responses

Three baseline injury responses are above the maximum allowed. Therefore this is not a feasible design.

The primary goal of the DOE was to explore the design space to find the most dominant design variables for occupant injury criteria. Only these dominant design variables would be included in the optimization process. This would reduce computational time considerably as one additional design variable would require 12 additional experiments.

Based on the latin hypercube sampling method 96 experiments were simulated. That is a total of 288 simulations considering 3 test modes. 2 feasible designs were discovered based on the DOE. Injury responses for these designs are compared to the baseline in Figures 8,9,10.

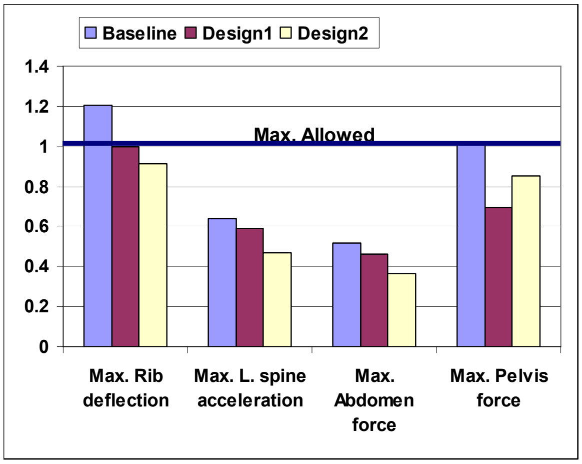


Figure 8. New 214 – Designs obtained from DOE compared to baseline.

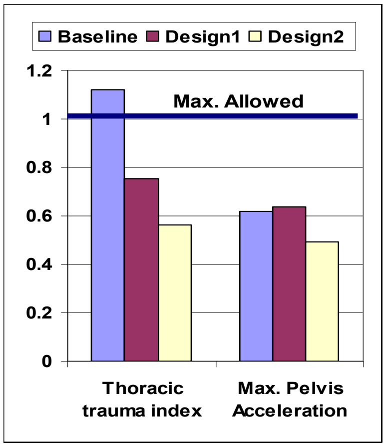


Figure 9. SINCAP – Designs obtained from DOE compared to baseline.

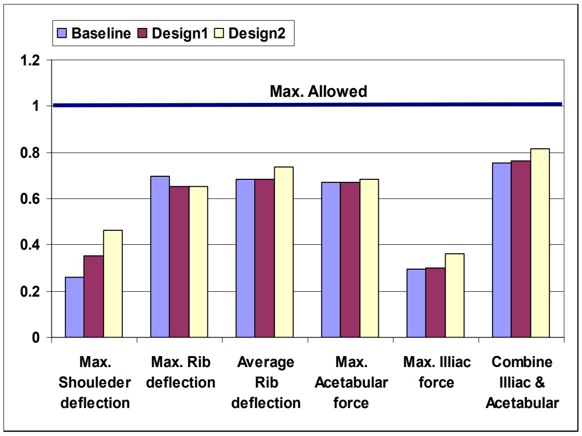


Figure 10. SICE – Designs obtained from DOE compared to baseline.

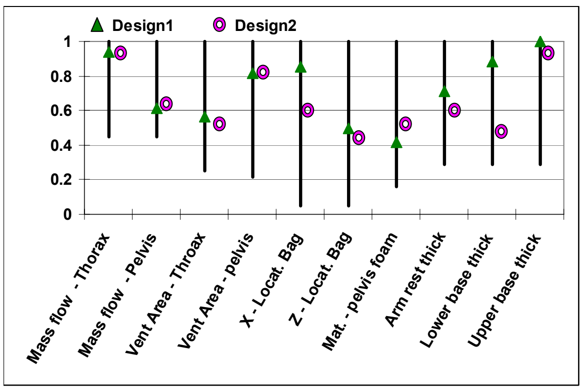


Figure 11. Feasible Design1, Design2.

Feasible Design1 and Design2 from the DOE have higher mass flow rate for thorax (see Figure 11). To achieve this level of mass flow rate, a higher pressure rated inflator would be necessary. This would be quite costly, thus not the anticipated solution.

A correlation value matrix which was generated based on the DOE gives information on the level of correlation between the design variables and the responses.

Table 1.
Sample correlation values

	Vent area - thorax	Z – location of the bag
Upper rib deflection - SINCAP	0.808	0.022
Thoracic Trauma Index - SINCAP	0.748	0.026
Average rib deflection - SICE	-0.701	0.060

The correlation value is always between +1 and -1. A correlation close to +1 or -1 signifies that responses and corresponding design variables are mostly linearly related, while a value close to zero indicates that they are fairly independent. Table 1 show that the upper rib deflection-SINCAP is linearly related to the vent area-thorax because of the higher correlation value between these. Therefore the best way to influence the rib deflection is to vary the vent area. On the other hand, the location of the bag in z-direction has almost no influence on any of the occupant injury responses. Thus this design variable can be neglected during the optimization. Based on the low correlation values seen, 4 design variables were taken out of the optimization process.

OPTIMIZATION

The noisy, non-linear nature related to crash analysis reduces the utilization of gradient-based optimization methods. Therefore the global optimization method ‘Self-Adaptive Evolution’ is selected to drive the optimization. The Self Adaptive Evolution (SAE) strategy is directly based on real valued vectors when dealing with continuous parameter optimization problems. It is a multi-recombinant scheme based on a population of designs and this algorithm’s strategy is to imitate biological mutation and selection. Designs with the best fit from the current total population will be selected as the parents for the next generation. The multi-recombinant method used here selects multiple parents to generate one offspring. Mutation is independently applied to each design. This way old generation produces a new generation. The new generation fitness is then calculated and new offspring are made. The algorithm has convergence criteria, and for certain ranges, algorithm parameter values have been determined for improved performance.

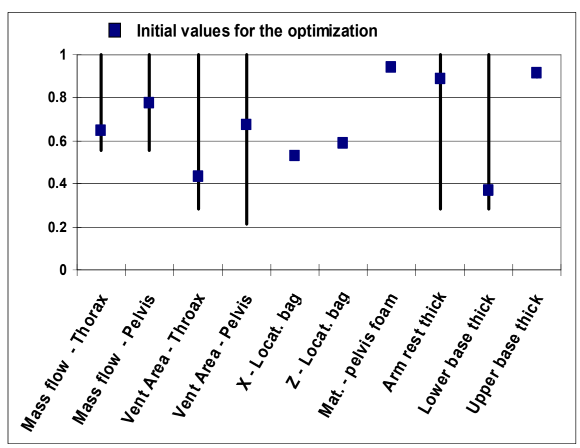


Figure 12. Based on correlation values. x, z-location of the bag, mat-pelvis foam and upper base thickness were taken out of the optimization.

The design range for the mass flow rate was reduced so that the same air bag inflator could be used. The list of experiments with this new range was found from the DOE without any additional computations. Out of these best doe experiment was selected as the starting point for the optimization. Although the global optimization method does not necessarily depend on the starting point, this will enable a faster convergence. At the start of the optimization 2 responses violate the constraints.

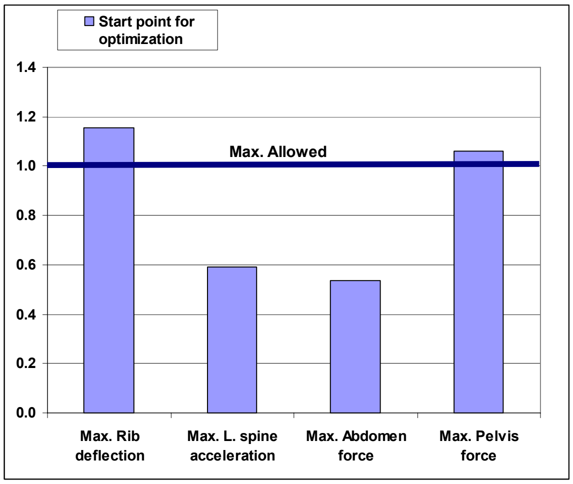


Figure 13. Two constraints were violated for New 214. SINCAP and SICE responses were with in the allowable range at the start of optimization.

The objective function for the optimization was based on the most critical responses. The responses selected for the objective function were thoracic trauma index from sincap, and max. rib deflection, max. pelvis force from new 214.

Objective Function: Normalized (Thoracic Trauma Index + Max. rib deflection + Max. pelvis force).

Six iterations were carried out for the optimization. A single iteration consists of 12 experiments. Therefore 72 experiments (a total of 216 simulations considering 3 test modes) were simulated. Following mass flow rate thorax vs pelvis section plots shows the optimization progress (Figure 14-19). The first and second iterations could not find any feasible design. The third iteration finds 2 feasible designs. The fourth iteration will focus more on these optimal regions. This leads to discovery of 2 more feasible designs. In fifth and sixth iteration the algorithm keeps focusing on this region and it discovers 7 feasible designs. Some of the iterations contain fewer experiments than the population size. This was due to some experiments failed due to model instabilities and was ignored by the optimization.

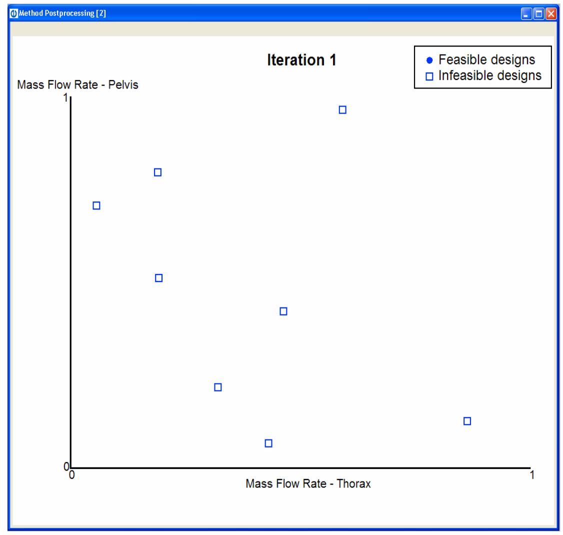


Figure 14. Optimization iteration1. No feasible designs were found.

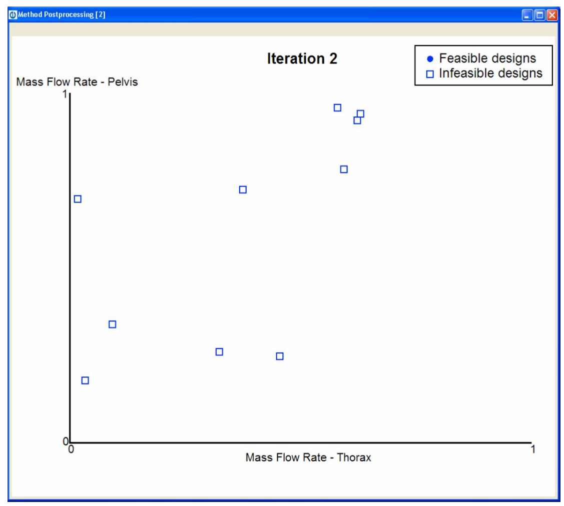


Figure 15. Optimization iteration2. No feasible designs were found.

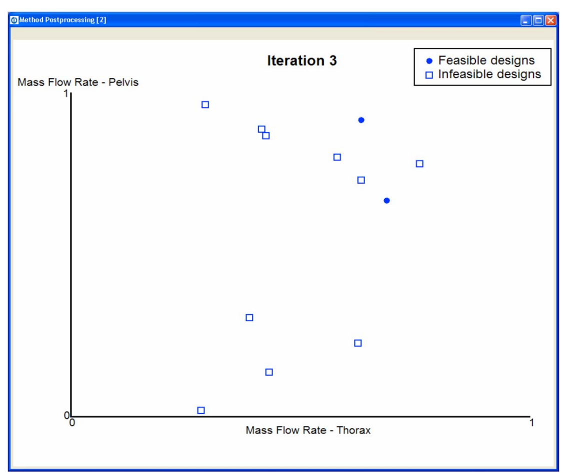


Figure 16. Optimization iteration3. 2 feasible designs were found.

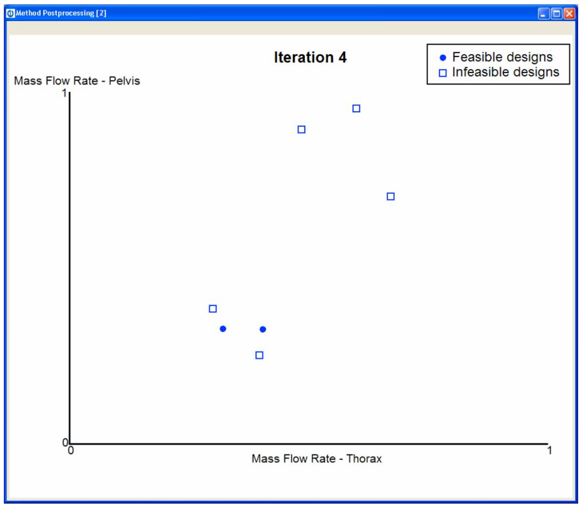


Figure 17. Optimization iteration4. 2 feasible designs were found.

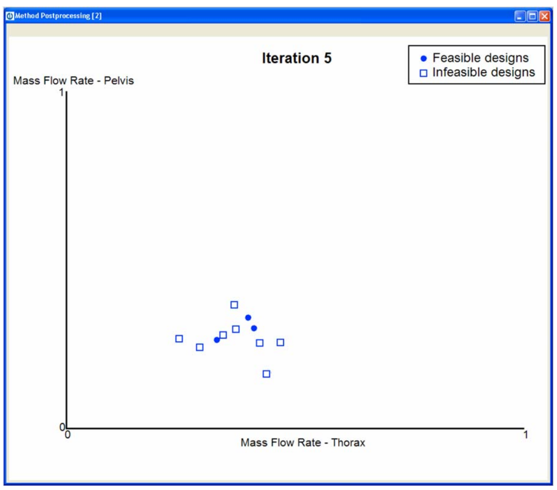


Figure 18. Optimization iteration5. 3 feasible designs were found.

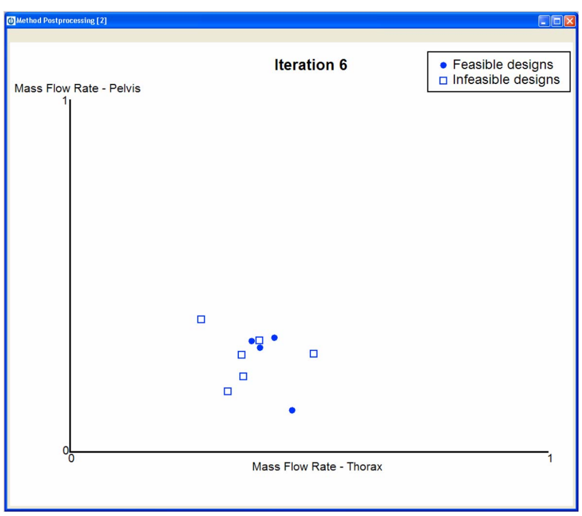


Figure 19. Optimization iteration6. 4 feasible designs were found.

The injury responses for baseline vs optimum design are compared;

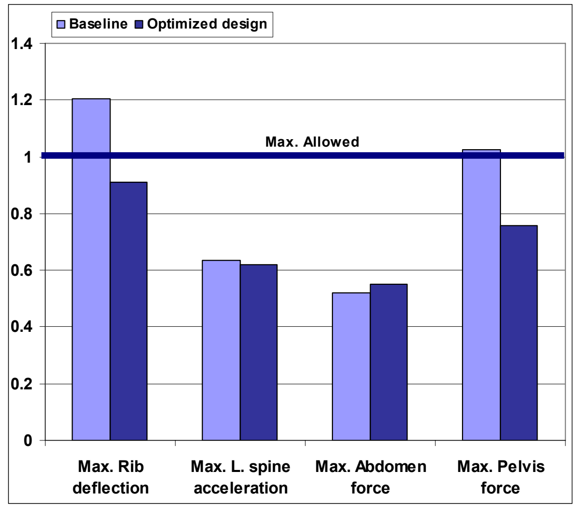


Figure 20. New 214: Baseline vs Optimized design.

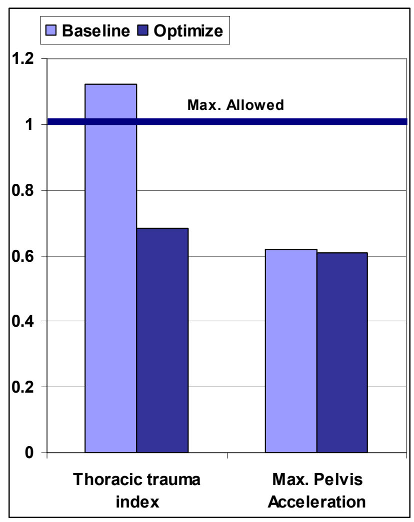


Figure 21. SINCAP: Baseline vs Optimized design.

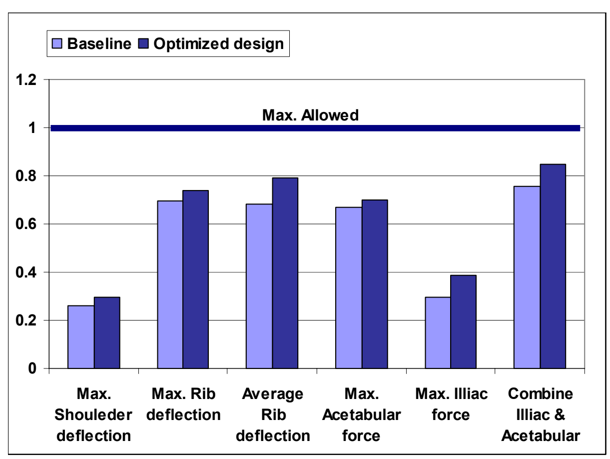


Figure 22. SICE: Baseline vs Optimized design.

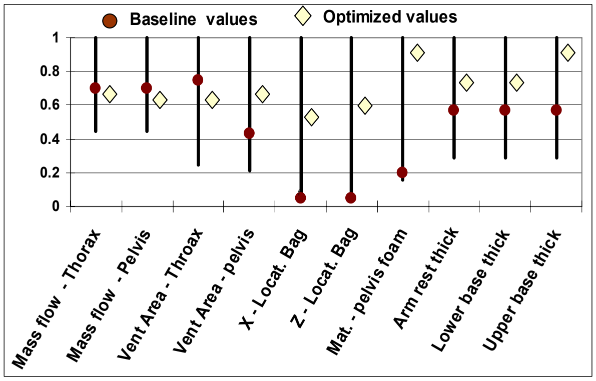


Figure 23. Comparison of baseline and optimized design.

Out of 11 feasible designs the most optimized design is compared to the baseline as shown in Figure 23. This optimized design does not require major modifications to the baseline design. Specially, the costly option of going for a new inflator is avoided. (Baseline and optimized design have similar mass flow rates). This optimum design was selected for further evaluation.

RESPONSE SURFACE METHOD

Response surface functions were developed by fitting taylor polynomial models through the DOE results for each of the occupant injury responses. AIC (Akaike's Information Criterion) procedure is utilized to optimize the quality of the models. These models were developed primarily to evaluate the fidelity of such functions for future work.

$$\hat{Y} = \sum_{i=1}^{p} a_i F_i(x_1, \ldots\ldots\ldots, x_n)$$

$\hat{Y}$ = Response

a_i = model coefficients are calculated based on the least squares criterion

x_i = Design variables

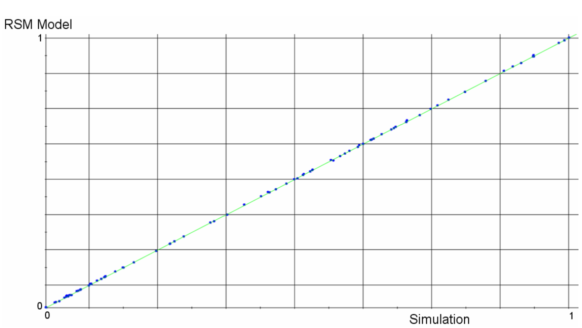


Figure 24. Scatter plot: Compares response values between simulation and RSM model.

The scatter plot assesses the quality of the models. Model is accurate when the sample points are close to the diagonal as shown in figure 24.

These models are quite handy to quickly identify design trade-offs. Once an anticipated design is found it should be verified by actual simulations. The optimized design was used as a sample point to check the RSM functions. Comparison is made between the actual and RSM prediction as shown below.

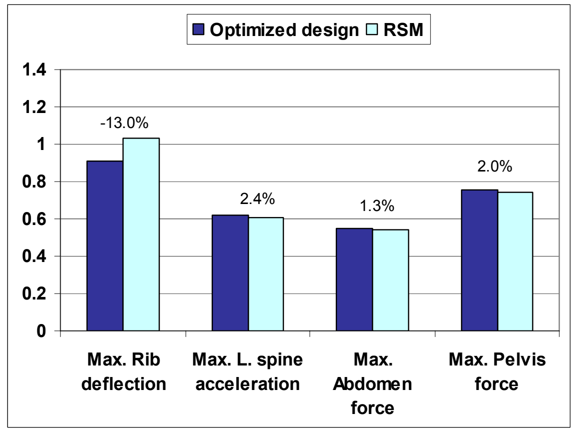


Figure 25. New 214: Optimized design vs RSM.

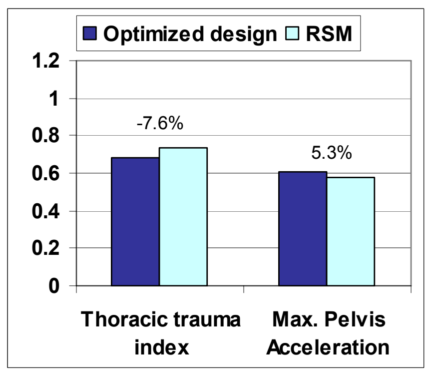


Figure 26. SINCAP: Optimized design vs RSM.

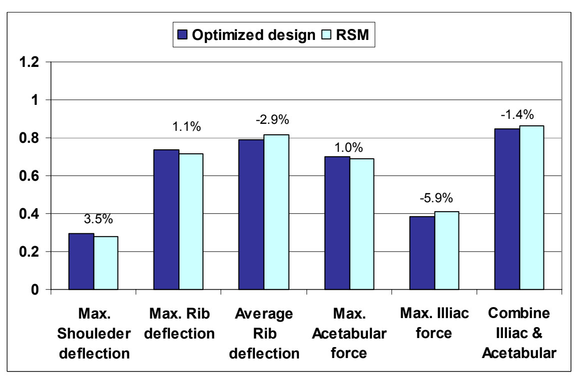


Figure 27. SICE: Optimized design vs RSM.

RSM predictions are acceptable for most of the injury responses except for max rib deflection (new 214) and thoracic trauma index.

RSM based optimization techniques were not explored in this study because crash analysis tends to be quite noisy and non-linear. Although reasonably good response surface functions were developed for many of the injury responses, they tend to be accurate along certain regions only. Therefore they are not recommend to be used with global optimization techniques.

CONCLUSION

The method presented in this paper shows how to employ DOE and optimization techniques to find a optimum restraint system that meets all injury requirements in a multi test mode scenario. Around 500 LS-DYNA simulations were needed to complete the study. OPTIMUS process automation software was used to integrate all 3 sled models into a single work flow which would make all simulations run in batch mode. A few simulations did not complete correctly due to model instabilities that occurred when extremes of the design space is explored. OPTIMUS was very flexible to incorporate safe guards that detect and eliminate the failed experiments from the optimization process. This is very important in optimization because successive iterations will depended on previous ones.

The methodology presented in this paper can be applied to any simulation based development work. DOE and Optimization technique that should be employed may vary depending on the nature of the application.

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