# OPTIMIZATION OF RESTRAINT SYSTEMS OF A VEHICLE ARCHITECTURE USING META MODELS

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Paper Number 11-0110

## ABSTRACT

In the coming years, car manufacturers will continue to diversify their fleet into an ever larger number of vehicle types. Cars will be developed with a focus on new special market requirements, responding to the customer's individual needs. Until now, at most 3-4 vehicles were derived from 1 backbone car (e.g. convertibles, coupes). In the future, however, there will be many different types of cars within a vehicle class (like the compact class). BMW is developing new solutions to deal with this increasing diversity. Each new derivative will be based on a uniform vehicle architecture and standardized construction kits.

In order to have sufficient functional degrees of freedom within this architecture, it is necessary to take all planned derivatives into account. Among other requirements, crash performance has a strong influence on the limitations of diversity.

This paper describes a new virtual method to optimize a frontal restraint system based on finite element vehicle models.

On the basis of a limited number of finite element simulations, response surface models were developed to identify and visualize the functional relationship between restraint system parameters and dummy responses. With these surrogate or meta-models, the optimization will be faster compared to the standard development process.

## INTRODUCTION

In recent years, safety requirements on the structure and the restraint system of a vehicle have increased due to legislation and the activities of advocacy groups. This trend will continue. Adaptive restraint control systems ensure an optimal performance in different crash scenarios: the airbag pressure after inflation may be chosen appropriately according to the passenger's size or the crash severity. Optimizing a highly adaptive restraint system with respect to all relevant load cases is already a complex task for only one vehicle type. In the case of an entire vehicle architecture, where the engineer needs to consider many vehicle types simultaneously, the developer will have to rely on additional specialized tooling.

Until recently, restraint systems were developed using rigid body simulation techniques. Now, full Finite Element (FE) simulations have become the state of art, providing better accuracy but also higher computational costs. Therefore, due to limited computational resources and the large number of required simulation runs, direct numerical optimization with these FE models is not feasible.

This paper describes how to tackle this high-dimensional and computationally expensive optimization problem. At first, the design space is scanned systematically by means of a design of experiment technique (DOE). Using this data, surrogate or meta-models (analytical nonlinear functions which approximate the relation between system parameters and dummy responses) are generated with which solutions may be computed very quickly. These substitute models are then used to run numerical simulations and to visualize complex functional relationships between system parameters and dummy responses. This is particularly valuable as it permits the user to relate the solution to his engineering intuition.

The paper is structured as follows: first, the essential mathematical methods and the basic idea of meta-modeling will be introduced. This topic includes beside the sampling method also the modeling quality measurement and a model fitting approach. The automated workflow at BMW will be explained. Afterwards, the benefit of the method will be illustrated by a practical example.

## METHOD

*Figure 1* shows the principle concept of a surrogate or meta-model. The FE models represent the unknown transfer functions (*Y(X)*) between the restraint system parameters (input vector *X*) and the dummy injury responses (output vector *Y*). Starting from a limited number of simulations, a surrogate model for each dummy response is built and can be used to predict various unknown design configurations without computing any further time-consuming FE runs.

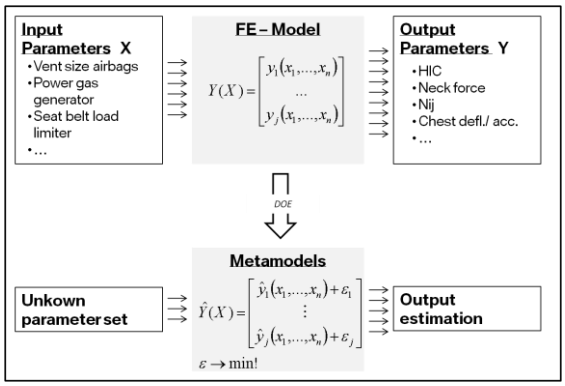


**Figure 1: concept of meta-modeling**

For each dummy response value *j* an independent mathematical surrogate model will be fitted to the sample points which were calculated using the FE model. The parameters of the meta-model will be chosen in such a way that the model error is minimized. In order to obtain an adequate accuracy for the surrogate model, a sufficient number of support points is necessary.

### Design of Experiments DoE

The method Design of Experiments (DOE) is a systematic approach to get the maximum amount of information out of limited number experiments, see [5]. The available DOE methods can be classified in two main categories: orthogonal designs and random designs.

Orthogonal designs (e.g. full factorial) distribute the support points such that they are statistically independent. As a major disadvantage, the number of required experiments grows exponentially with the number of dimensions (number of input parameters). An optimization of an adaptive restraint system with approximately 10 parameters would require $2^{10}$ or $3^{10}$ simulations for a 2- or 3-level full factorial, respectively.

Random designs are commonly used in crash applications with a large number of parameters. Random means that the parameter values will chosen by a random process. The most common method in crash applications is the so-called Latin Hypercube Sampling, which is based on the plain Monte Carlo method. A Latin Hypercube Sampling is constructed as follows: Let n be the number of designs that you are intend to simulate. Each parameter dimension will be divided into n equidistant levels. Within these subspaces, the parameter values are chosen randomly. Each design is a random permutation of design levels. This ensures that each level is probed in the design [5]. Furthermore, the limited number of sample points will be distributed over the design space in an optimal way. Practical experience in optimization of frontal restraint systems shows that 100 – 150 designs are typically enough to obtain predictable meta-models.

### Modeling

A separate FE Simulation is performed for each design of the DOE (i.e. a particular set of restraint system parameters). Each simulation takes approximately 5-7h on a HPC Cluster with 12CPUs (depending on the level of detail of the FE-Model). The sample points and the computed results are used to generate the approximation functions:

$$Y(X) \rightarrow \hat{Y}(X) \qquad (1)$$

In technical literature there is a wide range of approximation methods available. A commonly used method is regression analysis. Usually, the approximation function is a first or second order polynomial which is fitted to the support points. In case of smooth problems, the accuracy of the surrogate model improves with increasing number of support points. Depending on the order of the used polynomials, it may be possible to fit the approximation function exactly to all support points. However, for noisy data (e.g. data from crash analysis) there is a risk of overfitting. *Figure 2* and *3* show the regression of a 2-D and 3-D problem. In addition to standard regression analysis, BMW uses also the following approximation methods:

- Moving least square approximations (advanced polynomial regression)
- Fuzzy models
- Support Vector Machines
- Neural Networks

Further information about the mathematical background is available in [2] and [3].

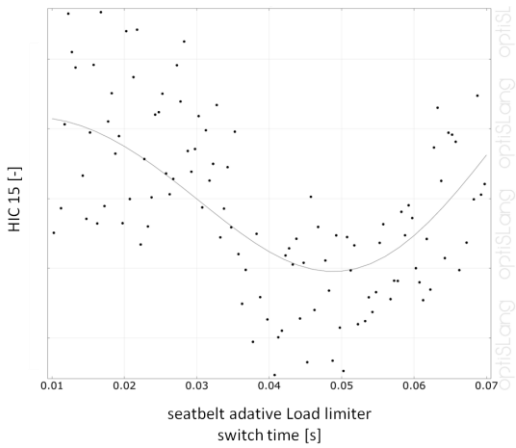


**Figure 2: HIC 15 Regression Analysis 2-D**

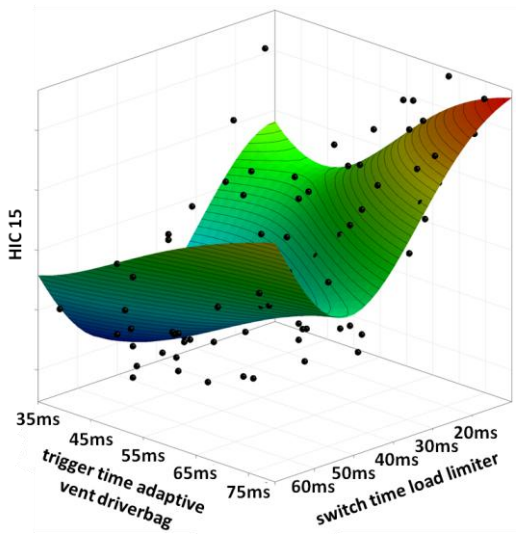


**Figure 3: Regression Analysis 3-D**

*Figure 4* shows the problem of overfitting with advanced polynomial regression (moving least square).

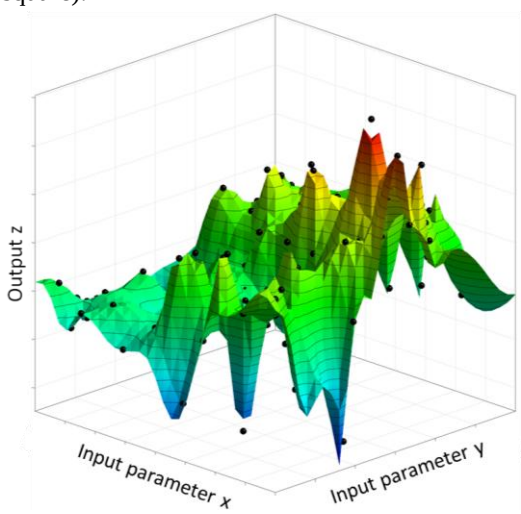


**Figure 4: moving least square with noisy data**

**Model Quality**

The accuracy of the approximation function with respect to the real problem has to be checked and verified. Appropriate error measures are necessary to assess the quality of fit. The most common value is the so-called Coefficient of Determination $R^2$ or COD. The COD describes the ratio between the variance of the model and the total variance of the observed data:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (2)$$

where $y_i (i = 1,\ldots,n)$ represents the true output values of the support points, $\hat{y}_i$ the predicted output values by the model approximation and $\bar{y}$ the mean value of $y_i$. If the variance between the predicted data and the real data is very small compared to the total variance of the sampling data, $R^2$ is close to 1, i.e., nearly 100% of the total variance of the problem can be explained by the meta-model.

Another measure is the mean squared error which is closely related to $R^2$:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (3)$$

The root mean squared error is the square of *MSE* and in the dimension of y:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (4)$$

The linear Correlation coefficient between the observed output and the fitted model may also be used:

$$Corr(y,\hat{y}) = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}} \qquad (5)$$

**Model Fitting**

As described above, it is always possible to get a perfect fit for a given set of values. In this case,

each calculated support point by the meta-model is equal the real physical value ( $y_i = \hat{y}_i \forall i = 1..n$ ). The error measures described would be 0 (*MSE, RMSE*) or 1 (*CORR*, $R^2$). A solution to this problem is the so called cross validation method. The principle idea is to estimate a model with a set of training data and then check the prediction on additional test or validation data. The error between the results of the approximation model and the true data will be used to optimize the model parameters and to compare different modeling approaches.

The selection of the validation or test data set is very important for the quality of the model. In our first approach the DOE data was separated randomly into training and test data. However, if the test data is not representative, a model with poor performance in the relevant region may be chosen. A common approach to avoid this problem is the use of cross validation: the data set will be divided randomly into, say, 10 equally sized subsets. In each loop *j* (*j*=1-10) the meta-model will be calculated without subset number *j*. This subset *j* is used as a test set. The 10 resulting error measures will be averaged, thus providing a reliable estimate of the model quality. In *figure 5* on loop of cross validation is shown.

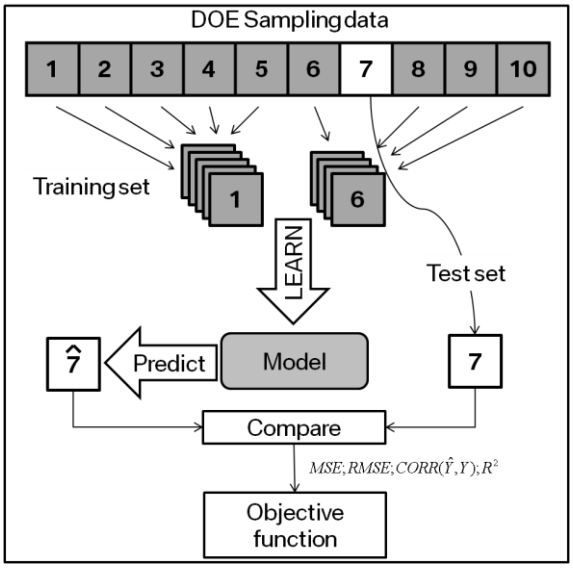


**Figure 5: on step of cross-validation**

*Figure 6* shows the complete workflow of cross validation to calculate the best model approach.

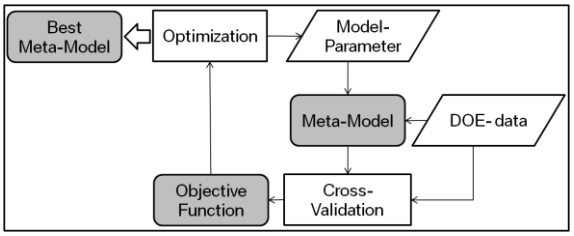


**Figure 6: concept of model fit**

## Post processing / Optimization

The first step in post processing should be a visual check of the DOE data. This is necessary to find numerical outliers and to check the plausibility of the data. Therefore, the time history data for each injury value is analyzed. With this, it is possible to differentiate between numerical problems and outliers due to physical effects such as bottoming out of the head caused by low airbag pressure. After a manual check of the DOE data an adequate meta-model will be built in the previously described manner for each required dummy output.

Two categories of post processing are available. The first possible way is the optimization "by hand". This means that the main dummy outputs (e.g. chest acceleration, HIC15, …) will be plotted in 2 or 3D response surface plots. These plots are 2 or 3D cuts in the multidimensional response surface. If the number of relevant parameters is small (e.g. 2 or 3), the user can find the optimum by looking at the plots. *Figure 7* illustrates this. Both diagrams show the relationship between the head acceleration (HIC15) and 2 restraint system parameters (seatbelt: switch time adaptive load limiter; airbag: power gas generator). In addition to the seat belt and airbag generator, the HIC depends also on the vent performance of the airbag. In the diagram on the left side, the trigger time of the adaptive airbag vent is very small (35ms). In the diagram on the right side, the adaptive vent is closed. As one can see, the smallest achievable injury level of the head (which is represented by the HIC 15) depends on the vent performance. These plots are particularly valuable, as they permit the engineer to visualize the potential of restraint system components and to relate the solution to his engineering intuition.

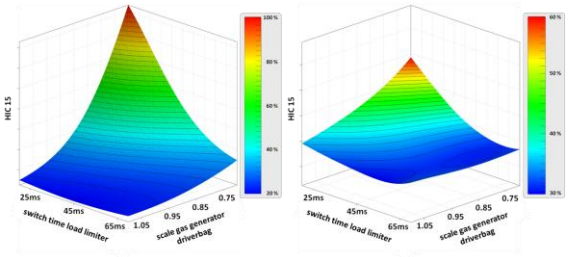


**Figure 7: visual post-processing with response surface plots (e.g. HIC 15)**

In case of parallel investigation of more than 1 vehicle it might be impossible to get an overview over the complete optimization problem. Therefore, it is possible to use standard numerical optimization methods to find the optimum. A common method is the Evolutionary Algorithm (EA). The optimizer uses the surrogate models to calculate individual parameter sets. Compared to a complete FE run a design calculation on the surrogate model takes only a few seconds. With this, it is possible to run a numerical optimization with multiple vehicles and load cases in an acceptable time (< 1h).

This approach, however, is limited: The optimization result is only as good as the prediction quality of the meta-model. This implies that the optimum is normally not better than the best DOE design. Therefore local optima of the approximation functions will always be in regions of DOE points. But nevertheless, the numerical optimization helps the user to find very fast the best solution with respect to additional constraints. When an optimum is found the last step should always be the recalculation of the parameter set by an additional FE run.

## Process Automation

To integrate the meta-model method into the standard development process, it was necessary to create specific software. The goal was to create a tool which allows the user to optimize their occupant models without requiring deeper knowledge of the described mathematical methods. The complete process workflow from the FE simulation model to the resulting meta-model is shown in *figure 8*. The user can control all steps very easily by means of a specific Graphical User Interface.

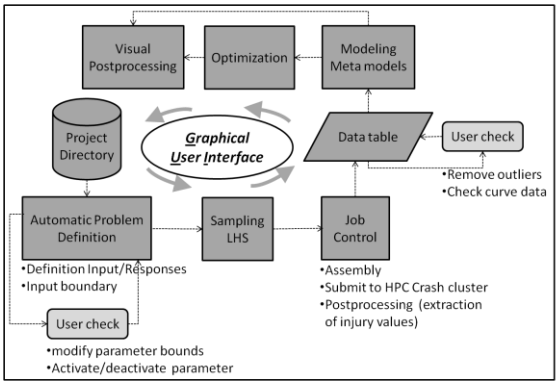


**Figure 8: Workflow Process**

The occupant simulation models have to be built in a particular structure, which is shown in *figure 9*. With this data management, we are able to optimize the restraint system simultaneously for multiple vehicle configurations of one architecture.

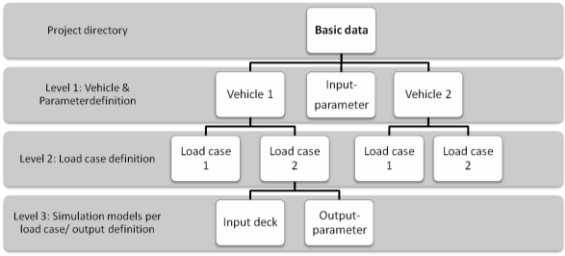


**Figure 9: Project structure**

## EXAMPLE

The following example shows the practical benefit of using the meta-model technique in the development process of a restraint system for 2 different vehicles (driver side only). Three main load cases from FMVSS208 were investigated simultaneously:

- 35mph Hybrid-III 50% (AM50) belted, rigid barrier 0°
- 35mph Hybrid-III 5% (AF05) belted, rigid barrier 0°
- 25 mph Hybrid-III 50% (AM50) unbelted, rigid barrier 0°

The differences in the vehicle geometry are shown in *figure 11*. Derivate 1 (red) contains a classical sedan seating position with a flat steering column. The second vehicle (black) is a small SUV with a higher seating position (command position) and a larger angle of the steering column. Both vehicles have different crash pulses.

In *Table 1*, the considered restraint system parameters are shown and classified. Some

parameters like the airbag generator power are equal for both vehicles in all load cases. Other parameters can be chosen independently for each load case.

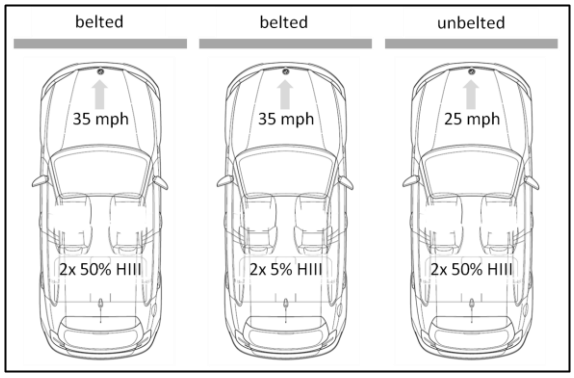


**Figure 10: test condition system optimization**

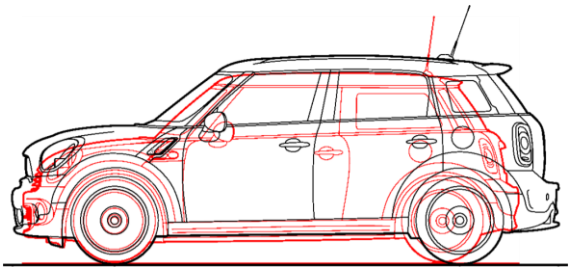

**Figure 11: geometrical range in derivates**

**Table 1: overview system parameter**

| | Vehicle 1 / 2 driver side | | |
|---|---|---|---|
| Restraint System parameter | HIII AM50 35 mph belted | HIII AM50 25 mph unbelted | HIII AF05 35 mph belted |
| *Driver airbag generator power | X | X | X |
| *Driver airbag Vent size | X | X | X |
| **Driver airbag switch time adaptive vent | X | | X |
| *Kneebag Generator power | X | X | X |
| *Seatbelt load limiter Load level 1 | X | | X |
| *Seatbelt load limiter Load level 2 | X | | X |
| **Seatbelt load limiter switch time load level | X | | X |
| **Steering column Force level crash deformation element | X | X | X |

*) parameter equal for all vehicles (standard construction kit)

**) independent parameter adjustable for load case or vehicle

## Data base

The results of this study are based on validated occupant crash simulation models of both cars. As an example, one of which is shown in *figure 12*.

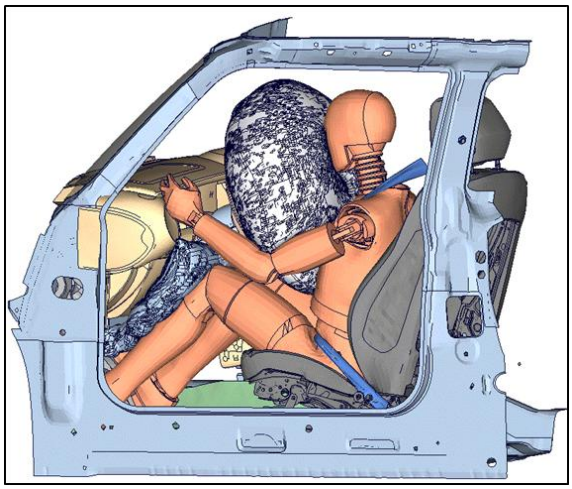

**Figure 12: CAE model driver side**

The evaluation of the simulation models includes the common injury values of the Hybrid III dummy which are specified in the FMVSS208. Therefore, every configuration has at least 11 injury values from different dummy regions (head, neck, chest, femur). In addition to the legal injury values, also the US-NCAP limits were considered for the optimization.
The resulting DOE table contains 11-15 dummy responses and 5-8 system parameters per load case. Therefore, approximately 85 meta-models were built. A DOE with 120 designs (6 load cases per design = 720 FE simulations) was automatically calculated on a HPC crash cluster.

## Results

To reduce the complexity of the optimization problem, the range of response values of the DOE was checked and compared to the legal limits. As an example, *figure 13* illustrates the results for one load case of vehicle 1. In this load case (AF05 35mph belted), 6 injury measures were close to the allowed limits. The most critical quantity is the chest acceleration which is in some configurations higher than the critical value (i.e. >80% of the legal limit). For this output, the meta-model was checked in more detail. In addition to the trigger time of the adaptive load limiter (when the force level is switched from high to low), the acceleration

depends also on the generator power of the driver airbag. All other system parameters have no significant influence on the acceleration level.

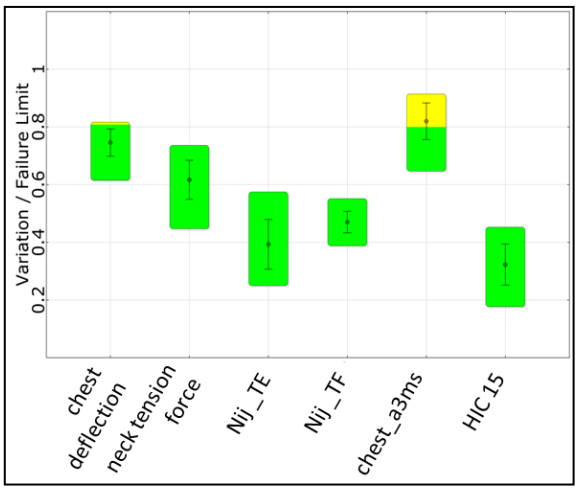


**Figure 13: most critical injury values vehicle 1 Hybrid-III AF05 35mph belted**

*Figure 14* shows the relationship between the chest acceleration and the 2 relevant system parameters. The blue and light green area of the response surface represents the feasible area where any choice of parameters will yield a subcritical response. Note that the generator power of the driver airbag will affect several load cases, however, the trigger time only this one. Therefore, the choice of generator power has to take all load cases into account.

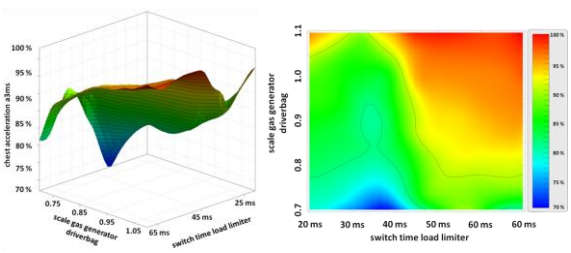


**Figure 14: relationship between chest acceleration, driver airbag and adaptive seatbelt load limiter for AF05 35mph belted in Vehicle 1**

To identify the most cross-linked restraint system parameters (i.e. having relevant influence on several load cases), all meta-models for the critical quantities were checked step by step. The conclusion is shown in *table 2*. The airbag generator has a strong influence on the chest acceleration in all load cases considered, and, additionally, on the HIC15 in the AM50 belted configuration. The influence of input parameters on the various load cases is shown in *figure 15*, illustrating the level of interdependency.

**Table 2: relevant restraint system parameter for most critical injury values**

| | Hybrid III AF05 35mph belted | | Hybrid III AM50 35mph belted | | Hybrid III AM50 25mph unbelted | |
|---|---|---|---|---|---|---|
| Restraint System parameter | chest defl. | chest accel. 3ms | femur force | chest accel. 3ms | chest accel. 3ms | HIC |
| *Driver airbag generator power | ++ | ++ | | ++ | ++ | ++ |
| *Driver airbag Vent size | | | | ++ | | |
| **Driver airbag switch time adaptive vent | | | | | | ++ |
| *Kneebag Generator power | + | | +++ | ++ | | |
| *Seatbelt load limiter Load level 1 | + | | | | | |
| *Seatbelt load limiter Load level 2 | | | | | | |
| **Seatbelt load limiter switch time load level | ++ | ++ | | | ++ | ++ |
| **Steering column Force level crash deformation element | | | | | | |

*) parameter equal for all vehicles (standard construction kit)

**) independent parameter adjustable for load case or vehicle

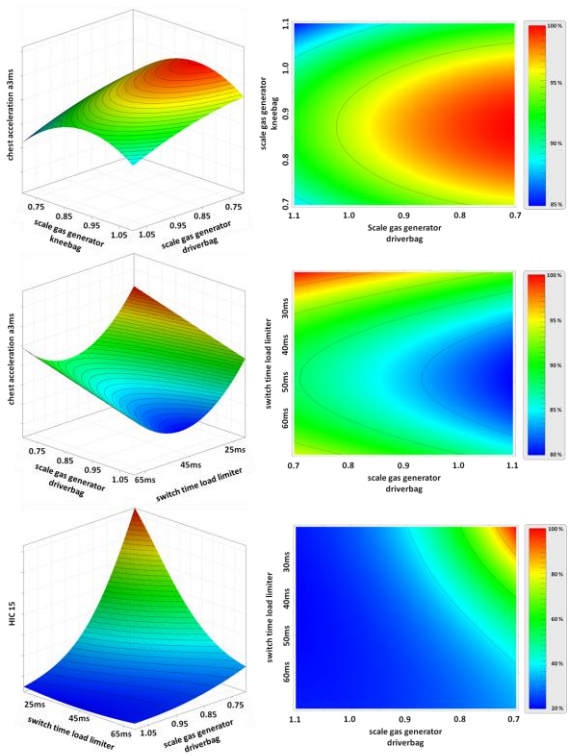


**Figure 15: relationship from generator power driverbag to chest acceleration (AM50 unbelted top; AM50 belted middle) and HIC 15 (AM50 belted bottom)**

The response surface of the other relevant load cases shows that the chosen gas generator power must not be too low. Especially for the HIC15 the

meta-model shows a risk for bottoming out of the head in combination with an early switch time of the adaptive seatbelt load limiter. Therefore a compromise for the choice of the generator power is necessary.

In addition to the manual optimization of the restraint system a numerical optimization of the meta-models was performed. The objective was minimizing the probability of injury according to the US-NCAP rating:

$$P_{joint} = 1-(1-P_{head})(1-P_{neck})(1-P_{chest})(1-P_{femur})$$

The injury risk values were calculated with the functions shown in *Table 3*:

**Table 3: injury risk curves for frontal impact AM50 [4]**

| Injury Criteria | Risk Curve |
|---|---|
| Head ($HIC_{15}$) | $P_{head}(AIS3+) = \Phi\left(\frac{\ln(HIC15) - 7.45231}{0.73998}\right)$ <br> *where* $\Phi$ = cumulative normal distribution |
| Chest (deflection in mm) | $P_{chest_defl}(AIS3+) = \frac{1}{1+e^{10.5456-1.568*(ChestDefl)^{0.4612}}}$ |
| Femur (force in kN) | $P(AIS\ 2+) = \frac{1}{1+e^{5.795-0.5196\,Femur_Force}}$ |
| Neck (Nij and tension/compression in kN) | $P_{neck_Nij}(AIS3+) = \frac{1}{1+e^{3.2269-1.9688Nij}}$ <br> $P_{neck_Tens}(AIS3+) = \frac{1}{1+e^{10.9745-2.375Neck_Tension}}$ <br> $P_{neck_Comp}(AIS3+) = \frac{1}{1+e^{10.9745-2.375Neck_Compression}}$ <br> $P_{neck} = \max imum(P_{neck_Nij}, P_{neck_Tens}, P_{neck_Comp})$ |

To find a solution which also fulfills the legal limits of the FMVS208, additional constraints were considered. Based on the meta-models, a numerical optimization with an evolutionary algorithm method (EA) was carried out. With 5000 runs (100 generations, population size 50) of the meta-models (total calculation time < 15min on a Linux workstation) the best value for the relative risk score was found. With the indentified parameter combination, all considered constraints derived from FMVSS208 (chest acceleration, HIC, etc) were satisfied. The convergence curve of the optimizer is shown in *figure 16*.

After the optimization an additional FE run was done with the indentified parameter configuration. The differences between the predictions of the meta-models and the true FE values are illustrated in *Table 4*. As one can see the predicted probability values were nearly the true values calculated by the FE simulation. A slightly higher delta is observed for the femur probability. The reason for that is a very low level of the femur forces caused by the use of a knee airbag. But the influence of this delta on the total probability is very small.

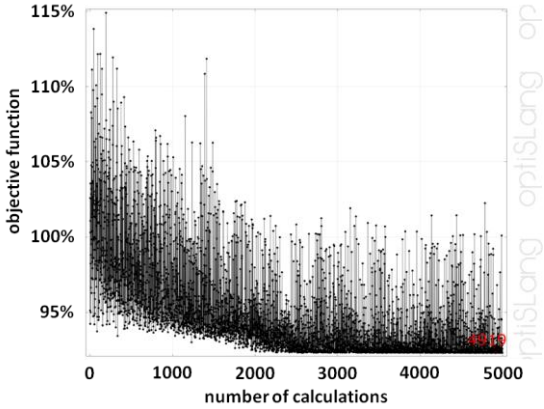


**Figure 16: convergence of the objective function (probability of injury)**

**Table 4: optimization result with meta-models and comparison to FE-simulation**

| | Δ FE simulation to meta-model | Contribution to P_joint |
|---|---|---|
| Probability of injury | +7% | - |
| Probability of head | +3% | 2% |
| Probability of neck | +1% | 45% |
| Probability of chest | +13% | 46% |
| Probability of femur | +30% | 7% |

## CONCLUSIONS

The described meta-model approach is very useful for optimizing restraint systems. Especially in the simultaneous optimization of more than 1 vehicle, the method helps to identify the important relationships. The influences of relevant system parameters (e.g. airbag performance) can be checked visually in different load cases. Thus, the method enables the user to find the best compromise satisfying all legal requirements and those of consumer tests.

Additionally, the method presented requires significantly less work than the standard development method without applying DOEs, meta-models and visualization tools (pre-/post-processing of FE-simulations).

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