Achieving Design Targets through Stochastic Simulation

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ABSTRACT

Engineers are usually confronted with performance targets for the systems that they design. Those targets may either be set externally (e.g. legislation) or internally (e.g. company standards). This paper shows how such targets can be achieved in a systematic way, using stochastic simulations. A major advantage of this method is that it enables the engineer to simultaneously assess the robustness of the solution, due to the fact, that scatter is taken into account. This is highly important, as the actual system will never work under ideal deterministic conditions, but in a stochastic uncertain environment. In addition to that, of course, the properties (material, geometry etc.) of the actual system itself always show a certain amount of scatter. Therefore a mathematically optimal solution that was established for the deterministic model only, in reality often proves to be non-robust as it reacts sensitively to scatter.

As an example a MADYMO occupant simulation will be shown, where an advanced driver airbag system is improved with respect to preset performance targets. The focus will be on reducing the occupant injury criteria levels by finding robust settings for the configuration of a new multiple airbag concept that is intended to improve protection in cases of high steering wheel intrusions.

INTRODUCTION

A typical engineering task during the development of any system, e.g. a car, is to improve its performance. This is done in order to meet design targets that are set either internally or externally. Improvements can be achieved by simply using experience based design rules or by using methods that systematically drive the system towards a better solution (=optimization tools). Very often it is tried to find an optimal solution for a system. Strictly speaking ‘optimal’ means that no better solution exists. Considering the complexity (and thus the vast number of variables) of the systems that are ‘optimized’ it is obvious that finding this solution is impossible.

But even if it were possible to find this solution, it would be of limited value, given the uncertainty or scatter of any system in the real world. While in the computer one can build (nearly) perfect models, real systems always have imperfections or deviations from the nominal state. So even if one finds the optimum for the computer model, one will not be able to build the actual product in exactly the same way and so one automatically gets sub-optimal solutions in practice. Optimization techniques ignore scatter of any kind in order to be able to build so called response surfaces. It is certainly possible to find an optimum on that surface, but once this solution is transferred back to the physical system its optimality vanishes because of the scatter which simply cannot be avoided. Then the performance may be far worse than expected.

In the light of these statements it seems to make much more sense to focus on robustness of improved solutions than on mathematical optimality. A solution that performs well even in the presence of scatter is clearly favorable to a fragile one that performs optimally under perfect conditions but performs poorly when scatter comes into play. Of course this does not necessarily happen, but the problem is that optimization tools neither proof the optimality of their solutions nor do they provide any information on the robustness of their solutions and therefore leave the engineer in a state of uncertainty.

The Monte-Carlo Simulation based stochastic improvement method described in this paper deliberately manages this uncertainty by introducing scatter into simulation models and enabling to quantify uncertainty in the results, i.e. in the performance of the simulated system.

Stochastic improvement differs from classic optimization tools in many respects:

· It acknowledges the fact that response surfaces are theoretical constructs, which do not exist in real world systems. The assumptions and approximations that have to be made in order to generate a response surface where actually only a scattered cloud of points exists are not necessary if one directly works with this cloud.

· Instead of calculating partial derivatives in order to move along response surfaces it uses the correlation matrix which shows how the parameters of a system influence each other.

· Instead of an objective function it requires the specification of a target. This means that the engineer has to specify a desired performance. From an engineering point of view this approach makes a lot of sense: Instead of letting a mathematical algorithm decide about the performance, the engineer should make a conscious decision how his system should perform. This approach certainly requires engineering judgement and experience. But the stochastic simulation method also provides the engineer with valuable information that helps define the target. The correlation matrix shows how the design variables influence the performance variables and also reveals dependencies among the performance variables. Based on this information one can define realistic and reachable targets

ROBUSTNESS

A well performing system is of little value if it performs so only under perfect conditions. If slight deviations from these conditions – which can never be avoided in the real world (only computer models allow these simplifications) - dramatically deteriorate the performance, a system is called non-robust. Robustness means finding an acceptable balance between the scatter of the inputs (=system parameters) and the scatter of the performance ([1], p. 63). We can not expect the performance to be always identical, but its scatter should be in the same range as the scatter of the inputs. If the system, for example, is subject to typical material and production tolerances in the range of 5-15% of the nominal value, and its performance scatter is larger than 50% we can speak of a non-robust design.

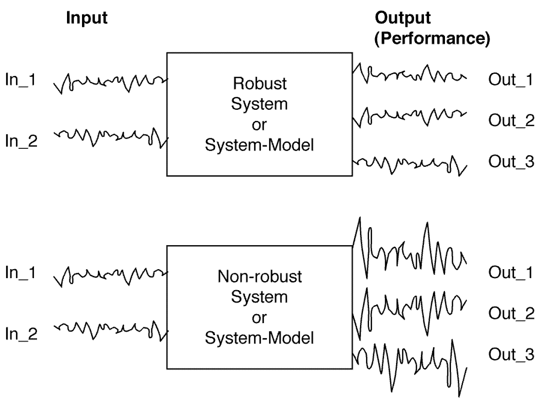

Figure 1: Robust vs. Non-robust System

A simple way to assess the robustness of a system is to compare the coefficients of variation (CV) for both inputs and outputs obtained from a stochastic simulation.[1] The coefficient of variation is basically the percentage of scatter (measured as the standard deviation) of a variable.

$$CV = \frac{s}{\overline{x}} = \frac{\text{Sample Standard Deviation}}{\text{Sample Mean}}$$

It therefore is independent from the magnitude of the variable and can be used to compare variables of different magnitude.

STOCHASTIC IMPROVEMENT

The stochastic improvement method is a natural and simple method.

A model is described by a set of input variables x_i and a set of output (performance) variables y_i . Most of the inputs are subject to random noise, i.e. scatter due to tolerances and imperfections. Some (typically only few) inputs are design variables; i.e. variables that can be modified - within certain limits – in order to improve the performance.

The improvement procedure implemented in the ST-ORM software package [5], which was used for the simulations described in this paper, works as follows [1]:

1. Define a target performance of the system; i.e. define for all or some outputs which is the desired value.

[1] For a brief description of the stochastic simulation method see [3]. Detailed explanations are available in [1] and [2].

2. Define the scatter (distribution) of the noise variables and define the scatter and the allowable range of the design variables.
3. Generate a random (Monte-Carlo) sample of models and run them through the solver.
4. For each model in the sample calculate the Euclidean distance from its result to the target performance.
5. Find the minimum distance; i.e. identify the model, which is closest to the target. If the distance is small enough, stop the process.
6. Modify the distributions of the design variables, so that the mean value is shifted to the value that was used in the closest model.
7. Go to step 3.

This method is also known as *return mapping* ([6], p. 140). The idea of the method is to shift the result cloud towards the desired point.[2] Due to the fact that for each step a cloud is generated it is possible to observe changes in the shape of the cloud. Sometimes the cloud becomes wider as it approaches the target – this indicates that the scatter increases. An initially robust design may turn out to become non-robust once it comes close to the target. Such important information is automatically generated during a stochastic improvement process.

As stated above no assumptions have to be made in order to use this method. Also the number of variables is nearly unlimited and does not influence the number of solver calls that is required ([1], p. 113). So one can define all variables that are stochastic in reality (=noise) as stochastic in the model. The number of actual design variables is usually relatively small for practical reasons, as not many things can be changed arbitrarily in a complex system such as a car.

[2] This target point may, of course, also be the result of a test! Then the improvement method is used to move the simulation model towards the physical test. This method is called ‚stochastic validation‘.

EXAMPLE: DESIGN OF A DRIVER AIRBAG SYSTEM

The following example will illustrate the application of the method using the MADYMO solver.

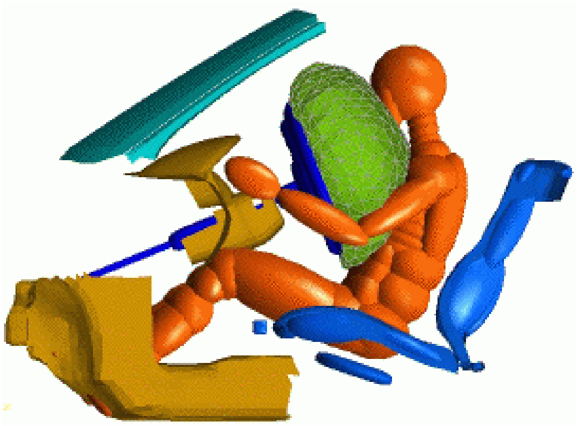

Figure 2: Asymmetric Driver Airbag

The starting point of the investigation is a driver airbag where diagonal straps are used to prevent the airbag from being pushed upwards by the occupant and the airbag itself is not concentric with the steering wheel but is mounted below the center of the wheel (Figure 3).

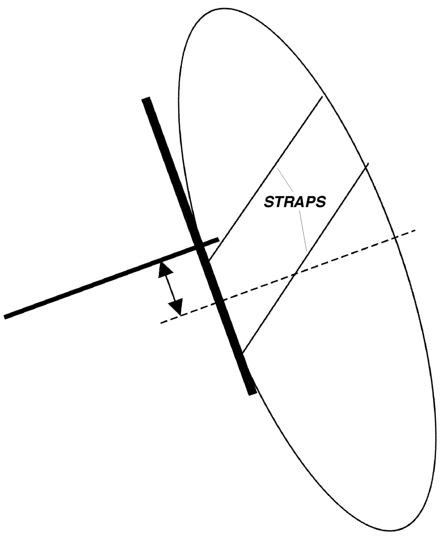

Figure 3: Asymmetric Airbag System

This system is obviously a perfect candidate for being non-robust. Though it works very well under nominal conditions, it is very likely to fail if the steering wheel is not in a perfect 0° position because of the asymmetry of the airbag.

The new Driver Double Airbag System (DDAS) concept, jointly developed by Eyrainer AutomotiveConcepts and EASi Engineering, is serving the same purpose of keeping the airbag in position. The DDAS includes an additional airbag located on top of the instrument panel. It fills the gap between the conventional steering wheel mounted driver airbag and the windscreen/roof of the vehicle. It has two important effects:

- It keeps the driver airbag in a low position so that it does not expose the lower steering wheel rim and
- it protects the head from windscreen contacts.

The potential advantage of the system that it is symmetric and thus its function is not depending on the steering wheel position.

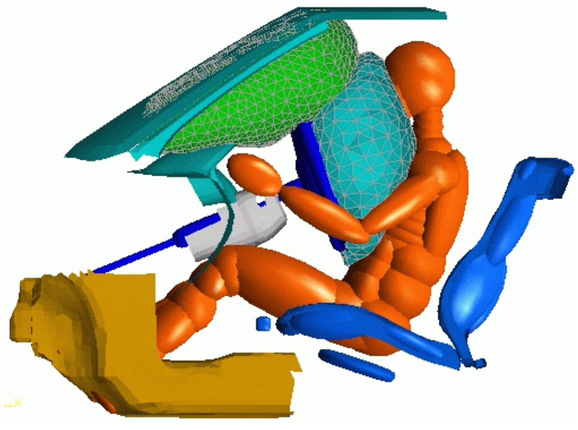

Figure 4: Driver Double Airbag System DDAS

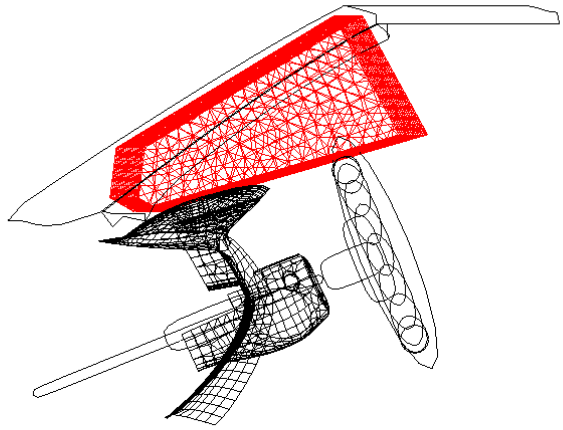

Figure 5: The DDAS-bag - reference shape

Let us first compare the two deterministic models. Figure 6 depicts some of the injury criteria obtained from MADYMO analyses of the FMVSS 208 frontal crash test at 30 mph. The asymmetric airbag performs slightly better. The DDAS, however, is a design draft, which is not yet optimized in terms of airbag shape, inflator and time-to-fire.

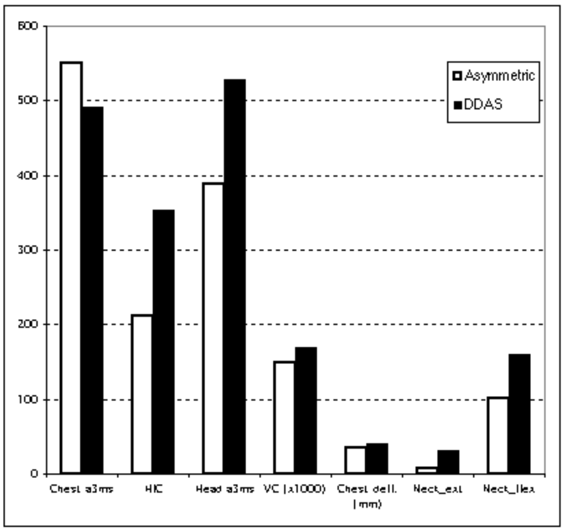

Figure 6: Comparison of the deterministic models

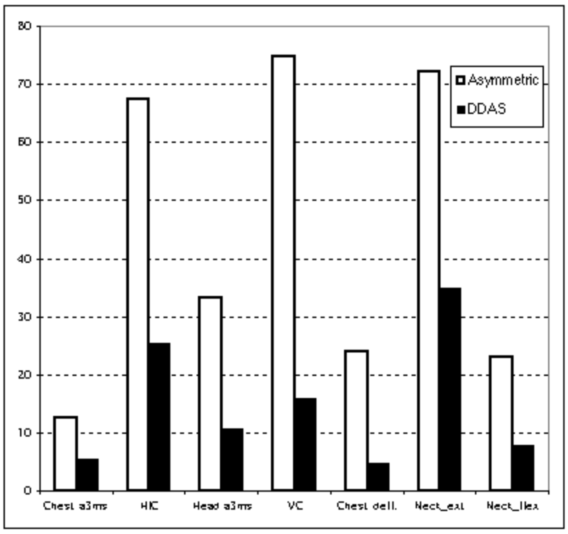

Figure 7: Comparison of the coefficients of variation (%)

It is, of course, much more interesting to compare the two systems under realistic conditions. Therefore scatter was added to many variables (including dummy position, airbag time-to-fire, airbag inflator, airbag vent size, steering wheel angle, steering wheel intrusion) in both models and a stochastic simulation with 100 shots was performed for each system. As it was of special interest a large amount of scatter (±180°) was defined for the steering wheel rotation. Even though this amount of scatter will not occur in the crash lab, it is a very realistic assumption if one considers real-world accidents.

Comparison of the coefficients of variation (%) of the two systems shows the advantage of the DDAS System in terms of robustness (Figure 7).

Figure 8 and Figure 9 show a more detailed comparison of the results of the stochastic simulations. The bars show the mean value for each parameter. The horizontal line indicates the nominal result from the deterministic analysis. The vertical line shows the range of results obtained from the stochastic simulation. All values are normalized (nominal result = 100%) for better comparison.

Again the lack of robustness of the asymmetric system becomes very obvious. But these charts yield another important information: The deterministic model of the asymmetric system is too optimistic as for nearly all criteria. Their mean value is significantly higher than the nominal result.

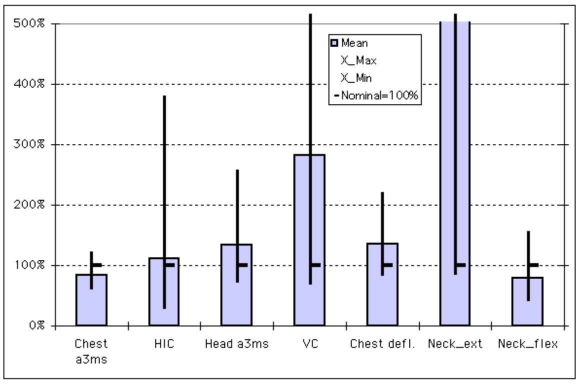

Figure 8: Injury Criteria - Asymmetric Airbag

In case of the DDAS the nominal and mean are nearly the same for all criteria.

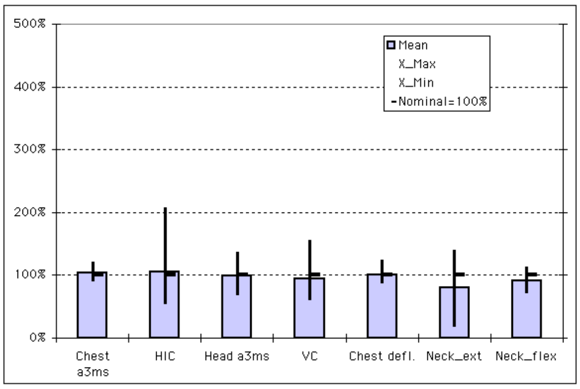

Figure 9: Injury Criteria - DDAS

One reason for the large scatter of the asymmetric system is the fact that in many cases (> 45%) the head impacts the windscreen resulting in high head accelerations and neck moments. Such contacts are completely avoided by the DDAS.

The next step is to further improve the DDAS' performance. As mentioned above, the model used for this study was only a draft design. Changes of the airbag shape and the inflation process (time-to fire, inflator, venting) should further improve the performance. Due to the simple shape of the DDAS bag, its parameterized geometry could be used as a design variable during the improvement process. Using the BAGGEN [5] tool the airbag was re-meshed after each geometry modification. The geometry was changed by moving point P4 horizontally and moving P5 horizontally and vertically (Figure 10).

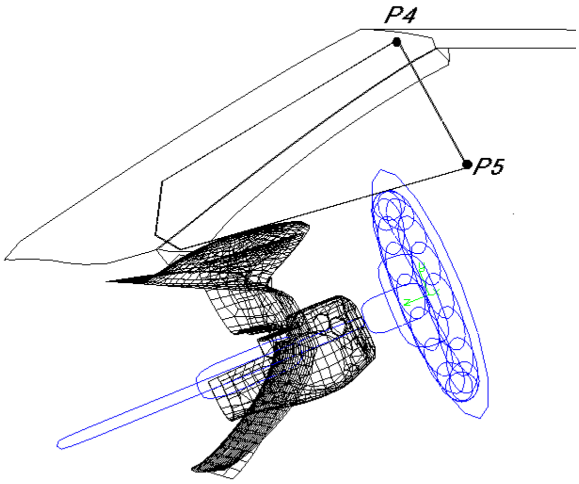

Figure 10: Geometry modification

The airbag was then scaled to obtain an initial geometry as the Initial-Metric-Method was used. The mass flow of the inflator was adapted to the modified size of the bag by calculating its new volume. The process is depicted in Figure 11.

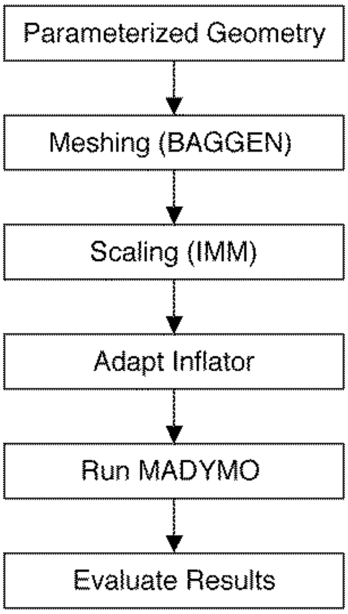

Figure 11: Model generation process

The performance target was defined as follows:

Chest a_{3ms} $\leq$ 450 m/s^2

Head a_{3ms} $\leq$ 400 m/s^2

HIC $\leq$ 250

VC $\leq$ 0,15 m/s

Neck ext $\leq$ 50 Nm

Neck flex. $\leq$ 190 Nm

After 3 iterations with 15 analyses each, an improved state was reached, which was also acceptable in terms of robustness. The target was not reached in all respects by the selected solution. But some solutions that were even closer to the target (see “best solution” in Figure 13) were not accepted as they were identified as non-robust. This is the great advantage of the stochastic improvement method – classical optimization would not have yielded that information.

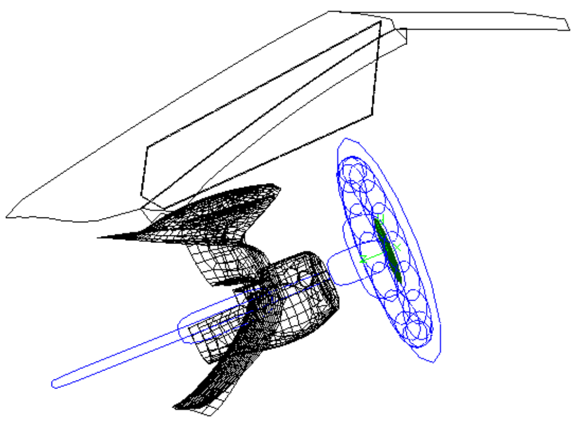

Figure 12: Modified Airbag Shape

The shape of the DDAS bag has changed significantly (Figure 12). In addition to that the time-to-fire of both airbags has been adjusted.

The improved system outperforms or matches the initial solution with respect to all selected injury criteria (Figure 13). Comparing the coefficients of variation one can see a slight increase in scatter. Compared to the asymmetric system the improved DDAS is still far more robust (Figure 14 and Figure 15). As the initial DDAS design, the improved design prevents head contacts with the windscreen.

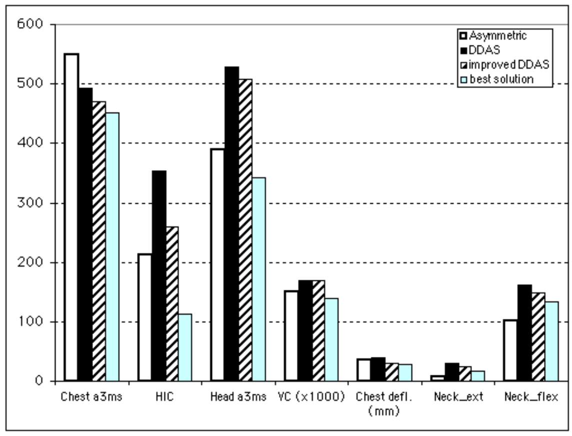

Figure 13: Comparison of the deterministic models

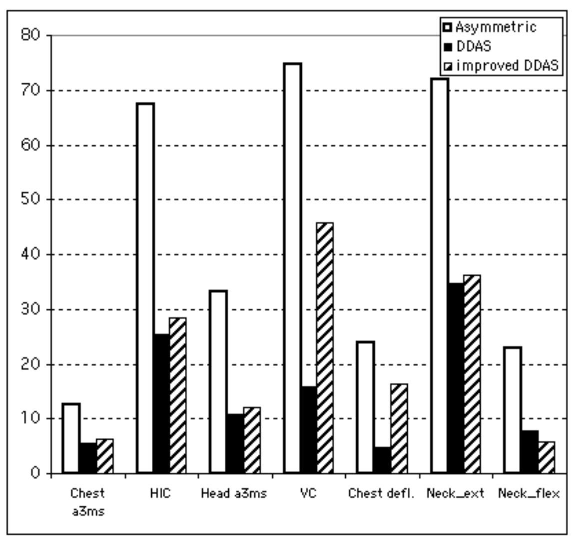

Figure 14: Comparison of the coefficients of variation (%)

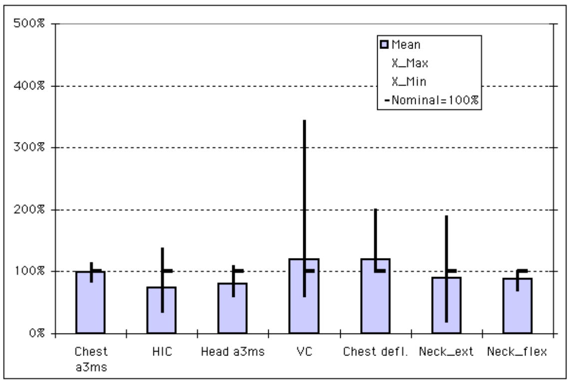

Figure 15: Injury Criteria – Improved DDAS

CONCLUSION

Industrial development should yield robust and reliable designs with desired performance levels in an uncertain environment. Instead of searching for a theoretical optimum, the stochastic simulation and improvement method focuses on meeting design targets and on finding robust solutions. It is a method that provides information on the quality of the solution that it finds as it quantifies the confidence that one can have in the solution. Using this method leads to designs that are fit for the real world and not only for the limited and idealized world of the computer.

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