Implementing Stochastic Multidisciplinary Design Improvement - Examples and Implications

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Abstract:

With the strength in managing complexity stochastic analysis offers unique characteristics for multidisciplinary design improvement. Therefore, the method has been used in large-scale multidisciplinary analyses, such as mass reduction while considering a combination of crashworthiness load cases (frontal, offset, side and rear impact) and NVH load cases (static and dynamic stiffness) in the same analysis.

How stochastic analysis introduces uncertainty and scatter, manages robustness, and the methods ability of handling complexity and many dimensions of a problem simultaneously, are some motives for its introduction. Both extensive computational and engineering process-oriented issues have to be addressed as a part of a solution.

This paper describes why stochastic analysis is used for multidisciplinary analyses in the automotive industry, and it summarizes some of the practical issues to be solved as a part of a solution implemented in contemporary development projects.

Keywords:

Robustness management, Risk management, Stochastic analysis, Multidisciplinary design optimisation, Robust design improvement, Bifurcation-driven, Mass reduction, Curse of dimensionality, Crashworthiness simulation, Occupant safety simulation, NVH simulation, Robustness studies, Safety engineering.

1 Introduction

Automotive design concepts are becoming increasingly more complex, with ever increasing demands of functionality, cost, reliability, legal requirements to be met within continuously shortened lead times. With this increasing complexity the development process becomes a balancing act between different solutions, their risks and consequences. To develop the appropriate level of knowledge to asses these risks and consequences enhanced design concept selections, reduced uncertainty, and enhanced analytical tools are required. And in order to avoid expensive late redesigns a combination of these enhancement with an increased level of cooperation and coordination earlier in the development process is needed.

To meet this need Multidisciplinary Design Optimisation (MDO) has been introduced. MDO has been defined as a methodology for the design of complex engineering systems and subsystems that coherently exploits the synergism of mutually interacting phenomena [1]. In the context of this paper MDO is a structured approach to automatically or semi-automatically perform optimisation or design improvement of a design, with a common goal definition, based on a combined set of load cases from different engineering domains. The value of MDO is to as fast and efficiently as possible, and without pre-assumptions, automatically validate design concepts and designs with their associated risks.

An example of MDO within automotive engineering is mass reduction of a complete car body-in-prime or body-in-white while considering crashworthiness and NVH characteristic in one analysis. Several different load cases for crash, for example frontal, side and rear impact are combined with several different load cases NVH and simulations of other functional requirements defined by the development project. The goal for an optimisation with this set-up is typically to reduce mass without a significant reduction in performance in crashworthiness or NVH characteristics. Mass reduction studies are becoming increasingly frequent, but hence this, and especially when referring to a full scale car crash model, it is considered an extensive analysis, in terms of size of the simulation and the complexity of the different models and load cases involved.

While traditional, deterministic, MDO methods have been successful in reducing the lead time in analysis of multiple disciplines, such as the example of mass reduction described above, they do not necessarily address all essential issues of automotive engineering, and especially not all essential issues relevant to automotive safety engineering [2) 3)]. Three highly relevant issues which often are ignored in traditional MDO are :

- How the increasing complexity of the design of automotive systems is addressed.
- How uncertainty and scatter in the properties of the simulated systems are introduced.
- How a large number of scattering independent and dependent properties are handled.

These issues are typically emphasized when the size of the problem is increased, and when the scope of the analysis is increased to cover multiple domains [4]. In order to address these, and other issues essential when performing large-scale MDO, EASi Engineering introduced Stochastic Multidisciplinary Design Improvement.

With reference to a number of recent successful implementations of stochastic multidisciplinary design improvement for the mass reduction case mentioned above, this application will also serve as an example for an explanation of how and why stochastic simulation is used for simulation over multiple disciplines. The key to an understanding of the strengths of the method is found in the basics of stochastic simulation.

2 The Basics of Stochastic Simulation

Under realistic conditions almost all properties of technical systems are subject to scatter. In a non-linear system, such as crash tests, even small variations in system properties can lead to significant variations in the behaviour of the system. Examples of properties which are known to vary are initial conditions, velocities, loads, manufacturing and assembly tolerances, material properties and boundary conditions. When these differences are taken into consideration, two physical systems will not produce exactly the same output.

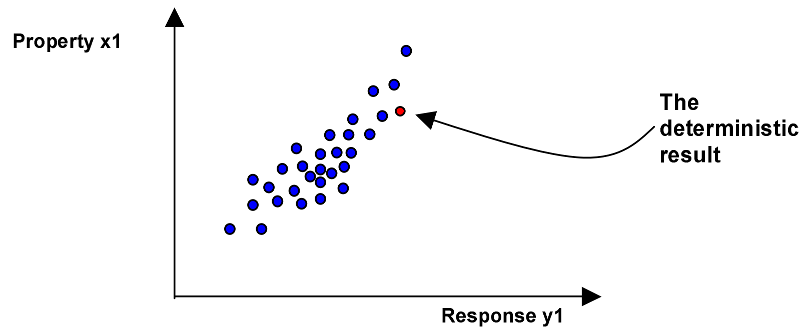

Fig. 1: The deterministic result and the response cloud when considering scatter.

Therefore, for a realistic representation of a physical system, a response is rather represented by a cloud of responses, than one single value. Stochastic simulation using the Monte-Carlo method is introduced in order to introduce this scatter in simulated systems. A comparison of the deterministic approach and the response cloud generated with stochastic simulation is depicted in figure 1 above,

The basic principle of stochastic simulation is simple: Based on a nominal initial model, a clone of this model is produced, substituting selected parameters of the model by random numbers that follow a random distribution. This procedure is repeated a number of times, in order to create random samples of the response. This basic principle is further described in Figure 2.

A typical sample size in stochastic simulation is between 15 – 100 solver calls, also known as repetitions, or shots. The exact number depends on the application of stochastic simulation, the general system robustness, and the accuracy required in the prediction of reliability. To determine the system robustness, which only requires the assessment of the response mean and median, only a limited number of samples are required. The number of iterations, and the cost in time and compute resources for their execution, is what appears to be a weakness of the method, but of course this cost has to be seen in the light of the additional answers and knowledge derived from the method. It should also be noted that all samples are independent. This means that in order to reduce turn-around time as many simulations as possible can be run in parallel. In an industrial setting this means that stochastic simulation can be fitted to the development projects expectations on response times, and the method can be economically justified with hardware resources such as Linux clusters.

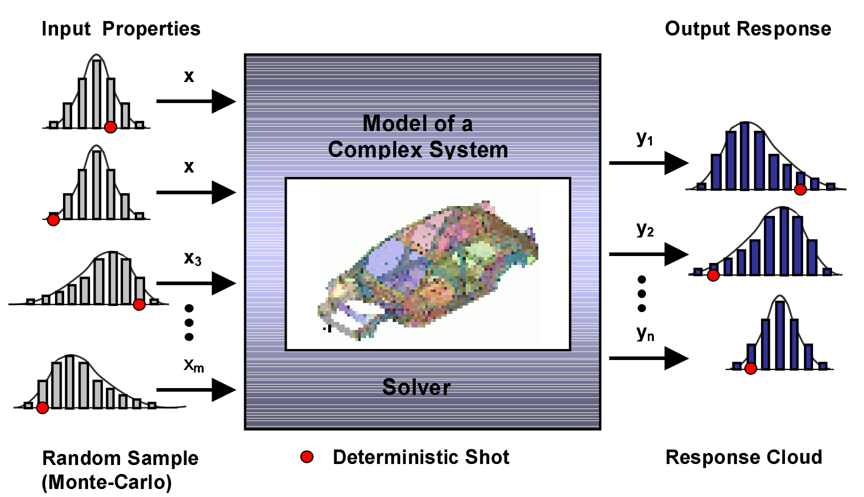

Fig. 2: The basic principle of Monte-Carlo based stochastic simulation.

The implementation of the Monte-Carlo method with large-scale finite element analysis in contemporary development projects is enabled by the software ST-ORM (Stochastic Optimisation and Robustness Management), developed and marketed by EASi Engineering. ST-ORM is used together with commercial solvers in order to:

- define,
- execute,
- post-process

, a stochastic simulation, as well as to perform stochastic design improvement. ST-ORM can be used with any solver which can generate input and output data in ascii-format.

As important as the introduction of scatter, stochastic simulation also introduces the possibility to assess and analyse the robustness of designs. Figure 3 describes the difference between deterministic and stochastic assessment of the result of a simulation. An arbitrarily selected response variable *y1* of a system is examined, and two different systems variations are compared. The limiting value *T* represents the maximum tolerable value, which means that the system will fail when/if *y1* > *T*. Assume that a deterministic simulation will generate the value *A*. The safety margin *s* for the value of *A* is *s=T-A*.

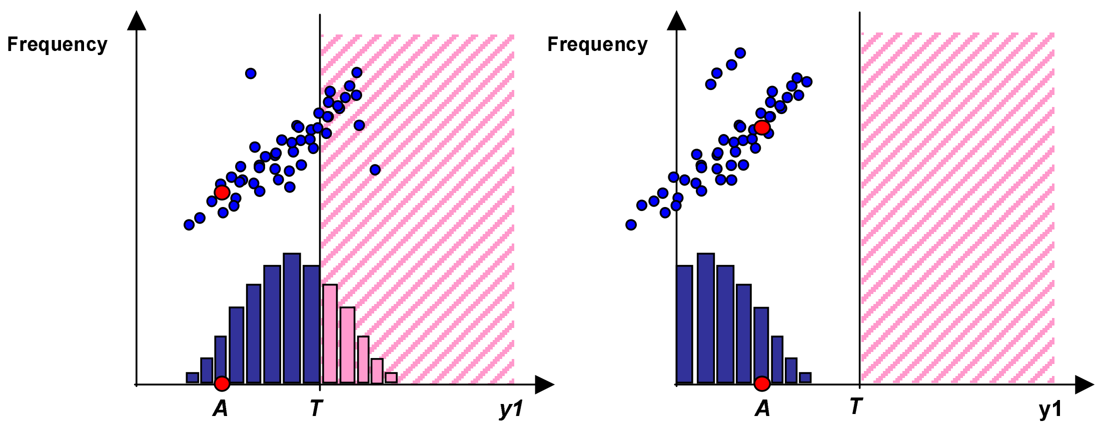

Fig. 3: Analysis of robustness.

The conclusion in a deterministic simulation is that the safety margins in both cases are acceptable. But if we complete the picture with the introduction of the response cloud, and the statistical description of this, a histogram, different pictures emerge. The left variant exceeds the limiting value in several cases, and therefore the probability of failure is very high. On the other hand, the right variant has a distribution within our defined safety margin, and within our limited sample there is no value which exceed the selected limit. An understanding of the complete statistical sample gives us a better understanding of the general system behaviour, including not only the knowledge about nominal functionality, but also the quality and robustness. The expected functionality is the most likely response, or the centre of gravity of the response cloud. The quality is expressed by the size of scatter, its diameter. The robustness is represented by the shape of the response cloud, and could be expressed in terms of stability, instability, bifurcations, outliers, clusters, etc. This understanding avoids the introduction of too excessive or inefficient safety margins, which would be the case if we only used a deterministic method.

This example is easy to follow, and the distribution is easily understood and described. In many real world situations the response clouds are not represented by ordinary Gaussian distributions, but rather by outliers, bifurcations and complex cluster patterns. This fact is extremely relevant to safety engineering, since a majority of crash applications are driven by local instabilities [5)]. This is especially true in fast non-linear phenomena common in safety engineering [6)]. In order to identify a response with such complex structure stochastic simulation is the only economically feasible solution available today. The ability of assessing the most likely response of a system, and the possibility to analyse how this response changes through changes in our system properties is the key to robustness management, and the key to stochastic optimisation.

3 The Basics of Stochastic Design Improvement

Stochastic Design Improvement (SDI) is used in order to improve the performance of a system while scatter in system properties are taken into account. The method is based on the same assumptions and reasoning as stochastic simulation. SDI is the method used for Stochastic Multidisciplinary Design Improvement.

As opposed to traditional optimisation, SDI enables the improvement of a system while the robustness is continuously assessed as a part of the improvement process. Instead of a focus on one optimum, SDI will find an improved state of the system while scatter in system properties is considered. Instead of finding the optimum it finds a solution fit to its purpose when a real world uncertainty has been introduced.

SDI as a method is an evolutionary method. A distinguishing characteristic of the method is that it deliberately does not introduce any assumptions or approximations regarding the simulated system. In a real design there are often few properties or Design Parameters which can be used in order to control the performance of the system. In parallel to the design parameters there is a larger number of properties which will have a strong impact on the performance of the system, but which are not within our control. These parameters are referred to as free stochastic properties, or noise.

The response in SDI is divided into Free Stochastic Response and Defined Target Response. The Free Stochastic Response is response which the user of the method track in order to confirm convergence, robustness, or other control response, while the Defined Target Response is the response which constitutes the target definition for design improvement. The basic principle of SDI is described in Figure 4.

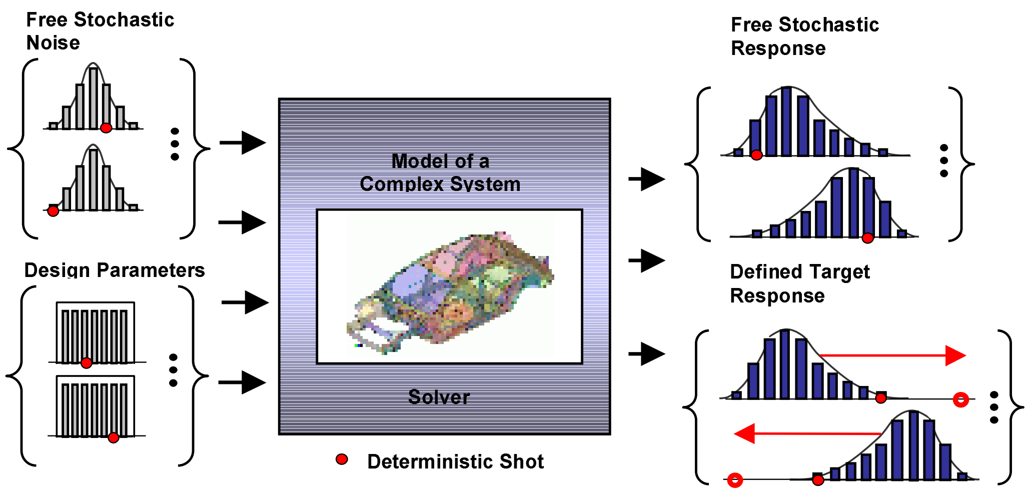

Fig. 4: The basic principle of SDI.

SDI is either implemented though Design Exploration or through Return Mapping. In Design Exploration a stochastic simulation is executed, in which the design parameters are allowed to scatter within the limits of the complete design interval. The different values of the design parameters are assigned in accordance with a uniform distribution. This procedure will scan the complete design space in order to reach an appropriate – improved – solution. The result of the scanning will show the direct improved solution immediately, the problem might be, of course that for a large design space, or a large set of possible combinations of design parameters and noise the time and resources to find an improved solution might be extensive. An alternative method called Return Mapping is therefore introduced. Instead of a screening of the complete design space at once it searches through the design space with stepwise iterations (referred to as runs).

Return Mapping starts with the definition of an initial state of a system and the definition of an objective target state. While in deterministic MDO the objective is to move a point towards an objective, in SDI the objective is to move the complete distribution to a robust combination of single target objectives. This is done through a formulation of single design objectives, not through analytical constructs such as objective functions and constraints. The target state is the weighted goal definition of different output parameters of an improved system.

As with the design exploration above the design parameters follows a uniform distribution while the noise is stochastic. After the initial definition of a start and improved state, a small sample is generated with minimal scatter around the initial state. Within this sample the distance within each case to the improved target in n-dimensional space is being calculated and a new sample is generated around the best case. This is done by shifting the average values of the design parameters to the value of the respective parameter came out to be in the best case. The iterations are continued until the improved target is reached, or until the state of the system is sufficiently improved. The procedure is illustrated in figure 5.

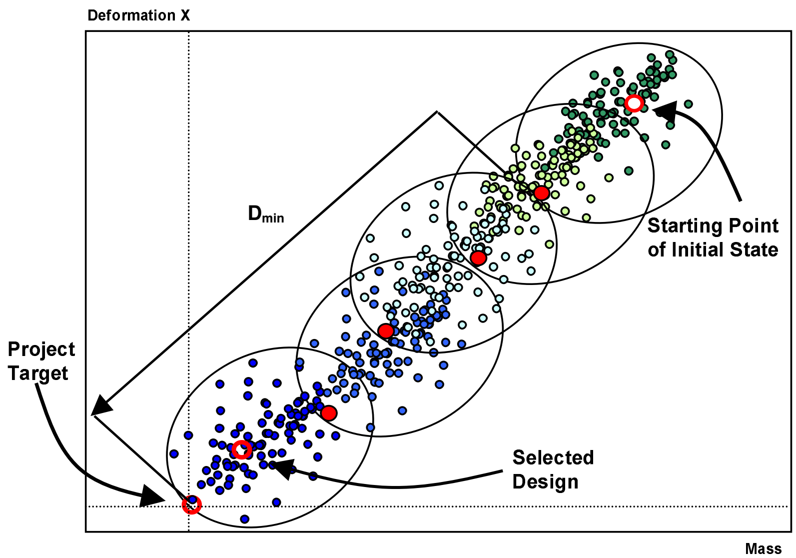

Fig. 5: Stepwise iterations of return mapping.

The important advantage of this method is how it handles robustness. And an effect of this is how the method deals with the "curse of dimensionality"[7)]. SDI is a one-dimensional problem. The stepping of the response cloud is based on a single scalar variable, the distance to the target state (D_{min}, in figure 5 below). This variable depends on all input parameters (both noise and design parameters) and all free stochastic response and the defined target response, or formulated through:

$$d_j = f(x_j. Y_j, y^*)$$

where *f* is a scalar function of its three vector arguments and the subscript refers to the sample number which minimizes the distance. Since these arguments are stochastic variables, also d_j *is* a stochastic variable. Therefore, a conclusion to make is that the return mapping method is independent of the number of noise and design parameters. For traditional MDO methods, exactly the opposite is true, these methods become computationally expensive with an increasing number of parameters [8) 9) 10)]. The reason for this is that with these methods, the majority, or up to 90% of the computational effort, is spend on the gradient evaluation. This gradient evaluation depend directly of the number of and the complexity of the parameters involved. This argument is one of the key arguments for the introduction of stochastic multidisciplinary design improvement.

4 Stochastic Multidisciplinary Design Improvement

Stochastic Multidisciplinary Design Improvement combines the different characteristics of stochastic simulation and SDI into a structured method for design improvement over multiple domains.

A typical application where the method has been successfully deployed is mass reduction while considering several load cases crashworthiness and NVH simulation. The thickness of sheet metal components are typically varied and responses due to multiple crash conditions and NVH cases are examined simultaneously, targeting towards a reduced mass while maintaining defined target values in all output parameters. The concept of Stochastic Multidisciplinary Design Improvement is outlined in figure 6:

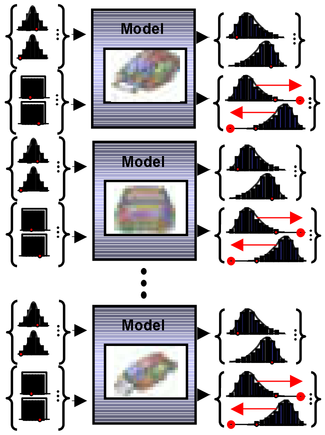

Fig. 6: The basic principle of stochastic multidisciplinary design improvement.

From an analytical point of view the basic principles of SDI through Return Mapping is applied with the only difference that the number of properties and solvers or load cases involved in the design improvement are increased. With reference to how SDI handles the "curse of dimensionality" highlighted above, this is not a computational or analytical issue, but primarily a practical issue of model synchronisation. When a load case is added to a stochastic design improvement this does not mean that the cost of the simulation automatically is increased due to the increased dimension, or that additional approximations and simplifications have to be made in order to adjust our resources to fit with the dimension of the problem. Rather, adding a load case will primarily only affect the practical definition of the problem, i.e. that an additional model has to be synchronized, and additional compute resources have to be allocated to cover for the execution of this specific load.

A typical set-up for a multidisciplinary mass reduction project is:

Load Case 1: Frontal Impact,	***1.000.000 elements, 400 CPU hours per shot.***
Load Case 2: Side Impact,	***1.000.000 elements, 270 CPU hours per shot.***
Load Case 3: Rear Impact,	***1.000.000 elements, 350 CPU hours per shot.***
Load Case 4: Static Stiffness,	***500.000 elements, 1 CPU hour per shot.***
Load Case 5: Dynamic Stiffness,	***500.000 element, 10 CPU hours per shot.***

The exact selection of specific load cases is defined by the development project. Each load case consist of a separate stochastic analysis, as depicted in figure 6 above. This is a requirement in order to consider the relevant noise and robustness in each load case or subdomain. The solvers used for crashworthiness and NVH simulation are typically MADYMO, MSC.Nastran, LS-DYNA, PAM-CRASH, and RADIOSS.

The target definition of the mass reduction will be:

Reduce mass of Body-in-white while the defined performance targets are kept constant.

The number of input parameters, design parameters and noise parameters is determined by their expected impact on the final design, and our experience or knowledge on their importance for system robustness.

The number of design and noise parameters in each stochastic load case is:

30 – 120 independent input parameters, 20-50 dependent input parameters

A majority of the design parameters are the material thickness of sheet metal components. Typical components selected are those which are know to have a considerable impact on the crash or NVH behaviour, for example longitudinals and the engine mount.

The separate parameters which constitutes the target definition represent a combination of different targets, some which are relevant for all load cases, or the global analysis, such as mass, and other which are only relevant for some subdomains and separate load cases. The number of responses or output parameters in each stochastic load case is:

20 – 70 output parameters; with 20 parameters used in the weighted target definition.

The parameters which constitute the weighted target definition are typically displacements, safety related parameters, or parameters related to energy absorption or torsional frequencies derived from modal analysis. Additional output response tracked is for example parameters for numerical control, convergence.

As highlighted above, introducing more load cases does not increase the analytical complexity of the design improvement as such, but as with any MDO it will affect the process of setting up an MDO project, primarily practical issues of administrative character, such as the definition of a synchronised product model of all load cases involved in the analysis and the allocation of the appropriate hardware and software resources for each specific load case. These and similar issues are managed through a correct execution process for stochastic multidisciplinary design improvement.

5 The Process of Stochastic Multidisciplinary Design Improvement

A mass reduction project is typically executed under time pressure and in a systems environment which include a rich set of different hardware and software platforms and perhaps some different queue systems and different queues in order to mirror different priorities and different resource requirements for the different load cases involved. Other complicating factors, especially in the start-up phase of the design improvement, are that some load cases might not have been verified for robustness prior to their introduction in the design improvement project, or that there are no consistent routines for the validation of the models, their execution, or their post-processing. Additionally, the hardware and software requirements for these analyses can for a majority of load cases be substantial. Methods for the reduction of inefficient use of compute resources, and wasted CPU cycles for non-convergent behaviour, have to be a part of a solution. The purpose with a coherent and structured process for stochastic multidisciplinary design improvement is to overcome these mentioned issues, and as fast as possible and with a high level of repeatability execute one or many design improvement runs.

Large scale mass reduction projects in automotive development processes are typically executed when a certain level of maturity in the simulation models and engineering knowledge has been reached. Due to resource restrictions the method is deployed when the data involved can be extracted and when there are resources allocated for its purpose. The figure 7 below gives an overview to when the different applications of stochastic simulation typically are applied in the development process.

The mass reduction project in itself is divided into three different phases. The first phase is the validation phase. In this phase all involved models, codes and procedures validated. For this purpose all different applications of stochastic simulation [11)], including stochastic model validation [12)] are used together with the basic functionality of ST-ORM used for test and quality check of complex multidisciplinary analyses (as illustrated by the arrows in figure 7). The use and integration of the different applications of stochastic simulation included in this phase is to clearly define automatic processes for the post-processing of all load cases involved. For example for NVH it is common to introduce routines for the automatic identification of the different modes to be tracked, and routines for handling this data has to be introduced and tested in the SDI process.

Since the optimisation method used relies on a rather simple set-up of randomising a standard deterministic model of a system, there is often a limited need for approximations and simplifications of model. This fact reduces the ramp-up of the mass reduction project significantly.

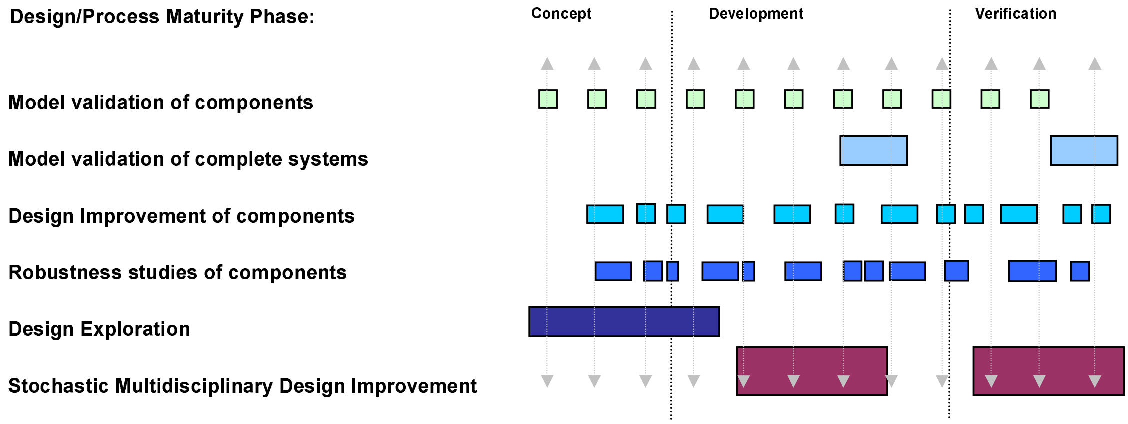

Fig. 7: Applications of stochastic analysis in the development process.

In the second phase of the mass reduction project, the development project has to agree on a common goal definition, and to guarantee that all models contains the same assumptions and product data, revision of material data, etc. This step typically also involves a first design exploration to test suggested concepts, and stepwise tests of sets of load cases. This phase of the design improvement is the most resource consuming, in terms of man time and engineering knowledge.

The third and final phase consists of a completely automatic procedure where the stochastic multidisciplinary design improvement is executed and monitored. The step involves the return mapping, which in a mass reduction case typically means 4 – 14 iterations with 12 – 40 solver shots in each iteration. This is the phase which is most intensive in terms of hardware and software resources, but it is often lighter than phase 2 in terms of man time and engineering expertise. An overview of resource requirements and the different phases of the mass reduction project is summarized in illustration 8.

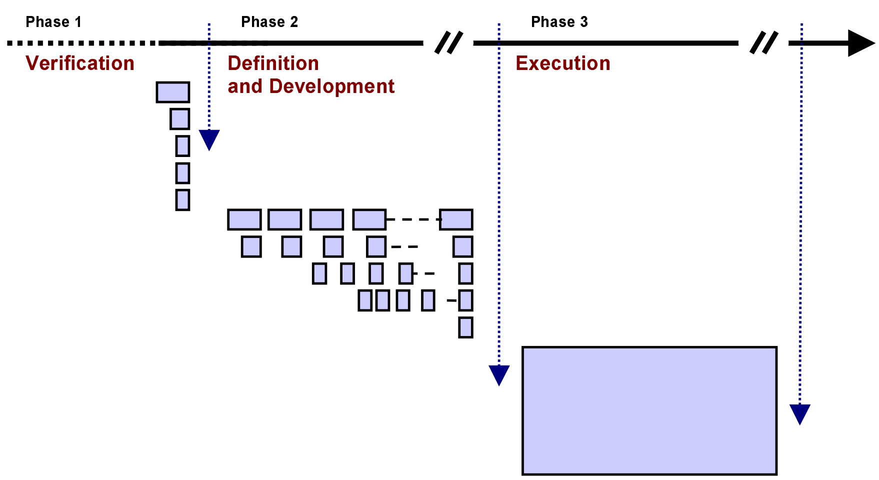

Fig. 8: Computational resource requirement of the three different phases.

In this final phase the target definition is continuously monitored and tuned. Engineering knowledge and decisions play an active role in this design improvement process. Depending on experience, preparations and availability of resources the complete process from phase 1 – 3 will require from 3 – 18 weeks.

An important experience is that the final target state is, even though reached, not necessarily the state which represents the design which is selected and implemented. The development project tends rather to select a design which is improved, robust, and often less optimal. This decision is made with reference to engineering experience, and it express the focus on fit, rather than optimal, solutions and designs.

The majority of practical issues have to be addressed though a correct Stochastic Multidisciplinary Design Improvement process, and through an appropriate level of functionality of the toolset used in order to define and manage the stochastic analysis. In the case presented in this paper the analysis is executed within an integrated framework for robustness, model validation and design improvement. Important characteristics of this framework are:

- Functionality to define dependencies and clear interfaces between solvers or load cases.
- Functionality to define break conditions if separate solvers, or group of solvers, fail.
- Functionality to stop separate solvers or load cases if unwanted values occur.
- Functionality for separate tests and iterations of single solvers or load cases.
- Functionality to easily manage and add different hardware and software platforms.
- Functionality to manage and easily add different queue systems and definitions.
- Robust internal functionality for distributed computing.

A summary of the key characteristics of the Stochastic Multidisciplinary Design Improvement process are:

- An integrated stochastic process.
- A high level or automation.
- Clearly defined processes and routines for test and analysis.
- Control of product configuration, models and dependencies.
- Cross domain communication and decision process.
- Appropriate sourcing in terms of knowledge, man hours, hardware and software.

6 Summary and Outlook

This paper has presented why and how Stochastic Multidisciplinary Design Improvement is implemented in large-scale automotive development processes. The strengths of the method and considerations made in its implementation have been exemplified with a multidisciplinary mass reduction project which covers different load cases crashworthiness and NVH simulation.

With reference to our experience since the first full-scale stochastic crash in 1997, and the increasing pace of adoption in industry, stochastic methods, once considered novel, are now applied in the general engineering work-flow in automotive and aerospace organisations. With reference to the presented application, its scalability and robustness in analysis, basic toolset and process, stochastic methods prove the maturity required for a rapid adoption in contemporary large-scale development processes.

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