Automated Metamodeling for Efficient Multi-Disciplinary Optimisation of Complex Automotive Structures

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Summary:

The use of multi-disciplinary optimisation methods (MDO) in the development process of complex automotive structures is often hindered by several problems. The required resources for very expensive simulations such as crash or 3D CFD analyses rapidly exceed the means available – especially whenever many input parameters, disciplines or load cases are involved. Furthermore, we have experienced that it can be difficult to assure stable runs of simulation processes over a longer period of time. As a result, ‚trivial' problems such as missing licenses, an overload in network or hard disk resources can lead to a termination of the optimisation process. Not to mention that an optimisation run based on different disciplines can only start once all disciplines involved have set up their respective simulation models. Even a simple change in only one affected discipline would necessitate the optimisation run to start from scratch (with simulations for all load cases/disciplines to be redone).

Here, metamodeling techniques can lead to a significant increase in efficiency since all information on the system behaviour gained from former analyses can be reused e.g. for optimisation runs or sensitivity analyses. In addition to this data storage functionality, the use of metamodels also decouples the occupation of computing resources from the actual use of the information. That means that idle CPU time can be used to collect more information on the product or system leading to reduced computation times in the actual optimisation method. Problems in particular simulation runs do not automatically result in a termination of the MDO method, but can easily be repeated. Consequently, it is also possible to evaluate the different disciplines independently even when other disciplines cannot provide a final simulation model yet. All these advantages together result in a much more efficient usage of computation resources.

However, the complexity and diversity of metamodeling techniques often prevent the potential user from these benefits. Typically, the choice between the different metamodel formulations is not easy to make.

In this paper, an approach is presented which allows for an automated model selection and fitting process. This approach enables the user to use metamodels rid of the complicated selection and fitting process. This task is undertaken by an optimisation algorithm which automatically generates a large variety of metamodels and accesses their respective applicability by means of statistics. As a result, the user gets the most suitable metamodel for each load case or discipline individually and in addition important information about the accuracy of the approximation.

The approach will be illustrated by a typical example of a multi-disciplinary optimisation of automotive structures.

Keywords:

Metamodel, automated metamodeling, multidisciplinary optimisation, MDO, surrogate model

1 Motivation for using metamodeling techniques in optimisation tasks

Today's engineering tasks strongly depend on complex computer simulations e.g. by means of FEM. In order to design highly competitive products, numerical optimisation methods are often used to improve the product performance or to reduce the related costs. For the design of complex car structures however, many disciplines play a role in the assessment of product performance. Here, multi-disciplinary optimisation runs (MDO) are needed which are typically complicated by some hurdles. The most prominent difficulty is probably the excessive computational effort related to time-consuming simulations such as crash or 3D-CFD analyses. Metamodeling techniques can significantly reduce this effort by exploiting a maximum of information that is hidden in the given data and by reusing this information for alternative designs. The complexity and diversity of metamodel formulations, however, impede many potential users to benefit from these advantages. Choosing a proper metamodel type is a difficult decision even for a metamodeling expert.
To overcome these problems, we propose an approach to automated model selection and fitting which accomplishes the demanding process of choosing the right model type and fitting it to the given data. Fully automated by an optimisation algorithm, many different metamodels are set up and the appropriateness of their approximation is assessed based on statistical quality checks. As a result, the user gets a particular metamodel for each load case and conclusions regarding the fidelity of the approximation. If such error estimations can be evaluated locally for a specific metamodel, these local error estimators can be used to refine the model constantly after each optimisation iteration. This sequential metamodel update helps to find a tried and proven optimal design.

2 Principles of metamodeling techniques

Metamodels are global approximations (also termed surrogate models) used as temporary substitution for the original simulation code [1]. A metamodel replaces the relationship between input and output variables by a mathematical expression that is much cheaper to evaluate. Usually, an individual metamodel must be established for each single response value. In general, the metamodel can be set up to depend on selected inputs only -- omitting those variables with negligible or no impact on the selected response.

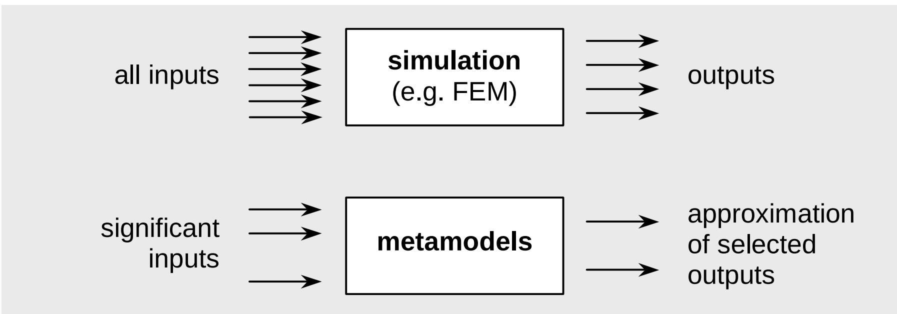

Figure 1: Metamodels as surrogate formulations for complex simulations

For the generation of a metamodel, an appropriate number of sampling points (the so called training data) is needed. These points can be selected via design of experiments (DoE) techniques [2] to gain a maximum of information about the characteristics of the underlying relationship between input and output. A suitable DoE technique must be carefully chosen since each type of surrogate model has need of different attributes with respect to the distribution of the sampling points. However, some DoE methods exist that are suitable for a large set of different metamodel types. Based on a proper DoE technique the original simulation is performed for the designs appointed by the coordinates of the sampling points. With the training data obtained from these computer experiments, the metamodel can be fit to provide an efficient estimate for the original function [3].

2.1 Pros and cons of metamodeling approaches

Metamodels are advantageous especially since:

- it is much cheaper to evaluate a metamodel than to perform a complex computer simulation. This yields a reduction in computational effort where many function evaluations are necessary (e.g. in optimisation or stochastic analyses).
- By use of metamodels, the designer can easily explore the entire design space to get a more profound understanding of the system under investigation.
- Metamodels can be used to combine information gathered from different sources, for instance analysis codes for different disciplines (e.g. fluids, structures, or thermo-dynamical problems), or physical experiments and computer simulations. An MDO in a typical simulation environment can only start once all contributing disciplines and load cases are properly defined i.e. a delay in one load case leads to a delay in the entire project. When using metamodels, the data mining is completely independent for all load cases involved, thus the first computations can start as soon as the first simulation model is ready. Especially, if some models proof to be incorrect at a later phase, only the affected metamodels have to be adjusted and the optimisation runs can be repeated (on the cheaper metamodels).
- Parallel computing is simple, since in general the individual sampling points are appointed simultaneously. Hence, the necessary computer experiments can be performed independently and in parallel.
- Metamodels can be used to smooth response values if noise is present in the observations.
- In addition, metamodels can help to stabilise the optimisation runs. In general, it is very difficult to assure a stable simulation environment. “Simple problems” like missing licences, overloaded networks, or filled hard disks can easily cause the entire optimisation run to abort. If such problems occur during the collection of training data ,it is very simple to repeat the related simulations.

The two main drawbacks with using metamodels are:

1. The fitting of metamodels produces additional effort and costs.
2. The question which metamodel formulation to choose for a specific application is not a trivial task. Even a metamodeling expert might have difficulties to pick the best model type.

To overcome these drawbacks, an approach will be presented next that disburdens the user from this crucial but complex problems. In *ClearVu Analytics* many different metamodels are computed with the help of an internal optimisation algorithm. Based on statistics, their applicability and accuracy for each particular response variable is checked. As a result, the tool proposes a particular metamodel for each load case and offers conclusions regarding the fidelity of the approximation. For use in an optimisation algorithm it might be interesting to use a metamodel that provides a local error estimation (like in the models underlying the tool *DesParO*). These local error estimators can be used to refine the model constantly after each optimisation iteration. Such a sequential metamodel update helps to find a tried and proven optimal design.

2.2 Automated metamodeling approach

For the automated metamodeling approach described above, *ClearVu Analytics* currently offers the following metamodeling techniques:

- Generalized Linear models [4]
- Support Vector Machines [5]
- Fuzzy models [6, 7]

Additionally, the tool *DesParO* provides a highly sophisticated implementation of radial basis functions (RBF). The list of available formulations is constantly updated to account for the latest developments in this fascinating field of research.

To find the best possible metamodel automatically and without user-interaction from a huge set of possible models types and parameters, two basic steps have to be performed:

1. In a first step, the free model parameters are determined for each available metamodel type separately. Here, a „mixed-integer-step“-optimisation based on a cross validation scheme is used. As a result, the best metamodel set-up for each class of metamodels is found.
2. Subsequently, all models that are „best-in-class“ are compared against each other to find the absolutely best model. The result of this investigation strongly depends on the method used to compare the models (hypothesis testing). The approach used in *ClearVu Analytics* can be found in more detail in [8].

3 Application example: multi-disciplinary optimisation of a complex automotive structure

To illustrate the usage of metamodeling techniques in a complex development process, a multi-disciplinary optimisation of a car structure will be given as an example.

The aim of the optimisation in this example is to reduce the weight of a car body by varying 96 sheet metal thicknesses. Five crash load cases and two NVH load cases are considered imposing in total 28 constraints. For this optimisation an existing set of training data should be reused that was collected during an earlier investigation [9]. The training data consists of 297 different combinations of sheet thicknesses which were generated according to a DoE scheme and a subsequent evolutionary optimisation algorithm. PamCrash and MSC.Nastran were used for the crash and NVH simulations. They were running on different computer clusters using different number of CPUs. The single simulation runs had execution times between 18min (static torsion) and 22h (front crash).

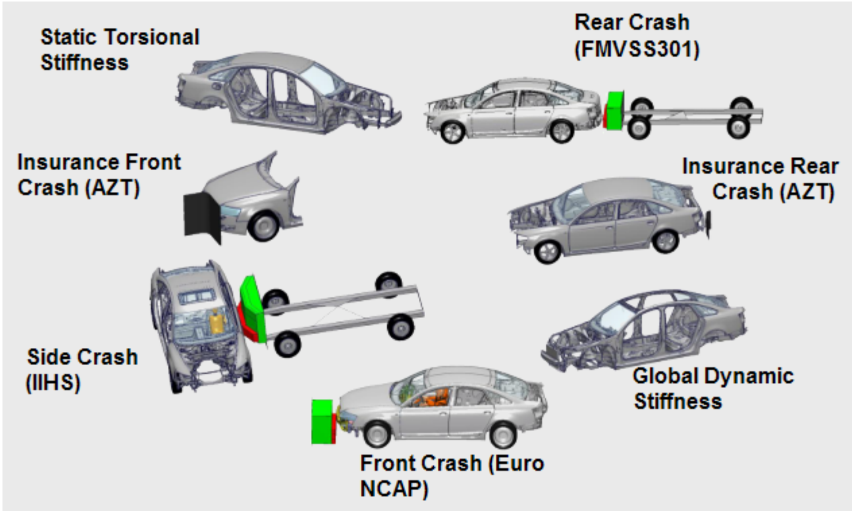

Figure 2: Disciplines and load cases considered for the MDO (from [9])

Based on this training data set, metamodels for all relevant output values (objective function and constraints) are determined. In the following optimisation, all underlying FE simulations are replaced by evaluations of the respective metamodels.

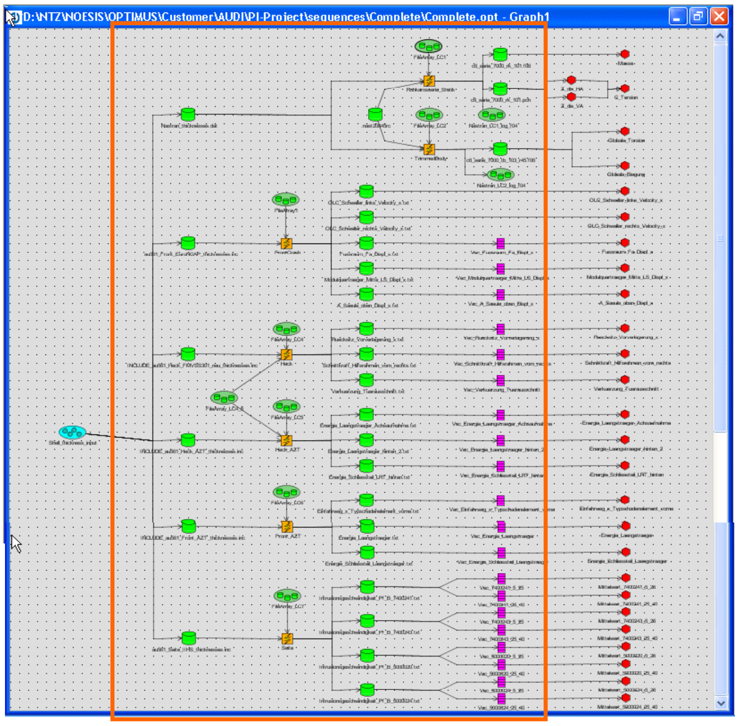

Figure 3: Workflow including crash and NVH load cases (orange box indicates part to be replaced by metamodel)

The fitting process in *ClearVu Analytics* proposes a linear model (type „generalized linear model") as the best model to approximate the relationship between mass and sheet thickness which correctly reflects the underlying dependency. For all other response variables (with are typically governed by significant non-linearity), metamodels of the type "support vector machines" (SVM) consistently show the best prediction performance.

The optimisation based on the fitted metamodels is performed in the workflow and process automation tool *OPTIMUS* with the gradient based algorithm *NLPQL.* The choice for this algorithm was made on the fact that all metamodels used for the current optimisation have a clearly defined gradient which is not spoiled by numerical effects (as often seen in results of explicit simulation codes). The optimisation converges in 10 iterations with about 1000 predictions per metamodel i.e. about 29'000

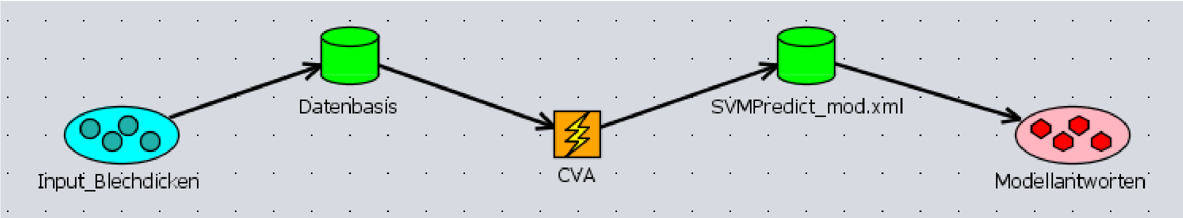

Figure 4: Workflow for MDO when using metamodels to substitute the original simulations

metamodel evaluations in total. The actual optimisation runs in this case takes about one hour where most of the time is spent for data transfer between *OPTIMUS* and *ClearVu Analytics* due to the fact that the interface for this prototypic application is realised by a simple ASCII file exchange. A more efficient integration is currently under development such that working on metamodels will be possible at real-time and optimisation runs will only take a few minutes.

4 Conclusions and outlook

From the preceding example the benefits of using metamodels in a complex simulation environment can be clearly seen.

1. In most instances the necessary simulations to assess the different design alternatives can be performed in advance and wherever applicable in parallel.
2. Metamodels represent a type of data storage and are not restricted for use in a specific optimisation but can be reused for alternative design studies or different optimisation runs (e.g. with modified constraint settings) without need for additional (expensive) simulations.
3. The diverse metamodeling techniques allow for an extensive study of the governing functional relationships. Based on the fitted metamodels design sensitivities can be computed or logical rules can be derived. In this way, advanced metamodels provide a tool to gain a deep insight into product behaviour.

Currently, a genetic interface of *ClearVu Analytics* and *DesParO* to well-established workflow management tools is under way and will be available in one of the next releases. This will complete the vision of metamodeling at the push of a button.

5 Literature

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