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Enabling Initial Design-Checks of Parametric Designs Using Digital Engineering Methods

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Abstract

The world consequently gets faster, so does product development. Therefore, the stock of development and simulation data increases continuously. Unfortunately, inexperienced users cannot cope with the rising number of simulation requests in the time needed. Digital Engineering opens potentials to support the users with newly developed methods and tools. In this contribution, we present a method to assist designers, inexperienced in finite-element simulations to perform an initial check of changed parametric designs independently, quickly and with support in interpreting the results.

Keywords: digital design, data-driven design, supportive technologies, finite element method (FEM)

1. Introduction

Product validation by simulation is an industrial standard for several years. Unfortunately, simulation experts are rare. Therefore, simulation departments are bottlenecks in most product development processes since they are involved in every iteration but are often understaffed or unexperienced. On the other side, the available pool of simulation data is growing and there are several powerful digital engineering methods to use those data automatically and support simulation or design departments (Kestel et al. 2016 and Spruegel et al. 2018). One promising approach is the democratization of simulation, meaning a frontloading of simulation tasks. The designer is enabled to produce simulation results by himself and thus perform initial assessments. The simulation specialist serves as an expert, provides assistance and performs the final validation. This procedure is, what we want understand as "initial design-checks" during this contribution. Another interpretation of initial design-checks may be in the context of early phases, which we explicitly don't consider.

One drawback of actual academic methods is, that they are encapsulated in individual systems. An embedding in a design process chain is missing so far. Our overarching vision, to which this paper is intended to make an initial contribution, is a system that provides end-to-end support for the complete development process, from the design engineer to the simulation specialist. In addition, possible tasks are automated or supported in a data-driven way.

In this contribution, we want to focus on the central research questions:

> *How can existing simulation data be used to realize reliable and easy-to-use initial estimates by the design engineer?*

In the remaining contribution, we take a deeper look at the state of the art of digital engineering and finite-element support tools in section 2. Afterwards, we present our concept for an adapted FE-toolchain in section 3 and a detailed look at relevant modules in section 4. In section 5, a demonstrator is shown, which makes use of the presented methods. A discussion and outlook in section 6 end the contribution.

2. State of the Art

2.1. Digital Engineering

Several authors try to define the term digital engineering clearly (Schenk et al. 2011, Schumann et al. 2011). We want to stick to the definition of Gerschütz et al. (2021) defining the term as the consistent evaluation and use of existing data from design, testing and operation using data-driven methods.
Those methods enable decisions based on data or even make autonomous decisions (Montáns et al. 2019). The most common terms in this context are Data Mining (Fayyad et al. 1996) and Machine Learning (Samuel 2000).
Metamodels are a combination of the two methods of Data Mining and Machine Learning (Gerschütz et al. 2021). Here, knowledge is extracted from existing data sets and applied with Machine Learning methods, resulting in a (meta)model to predict the behaviour of the finite element model. In the remaining contribution the term model will refer to the finite element simulation, the metamodel refers to the generated prediction model.

2.2. Finite-Element Analysis and Knowledge-Based Simulation

2.2.1. Finite-Element Simulation

In the establishment of virtual engineering in product development, new methods for simulating product behaviour were developed. There is a variety of options to choose from, depending on the specified challenge. For example, computational fluid dynamic simulations (CFD) are used to analyse wind or water disturbances in fluid mechanics. The methods in this publication refer to structural mechanics and, therefore, to finite element simulations (FE).
The finite element method describes the elastic or plastic properties of mechanical systems mathematically. A model is constructed from a limited (finite) number of geometrically simple elements to achieve this conversion. Since this model replaces the real component, it should reproduce its properties and geometry as accurately as possible. The goal of a finite element simulation is to represent the effects of loads on a body or an assembly. The representation of the results depends strongly on the investigated result variable, which can be, e.g. the occurring stress, the deformation or the natural frequency.
A typical process for this type of simulation is shown in Figure 1 according to Vanja et al. (2018).

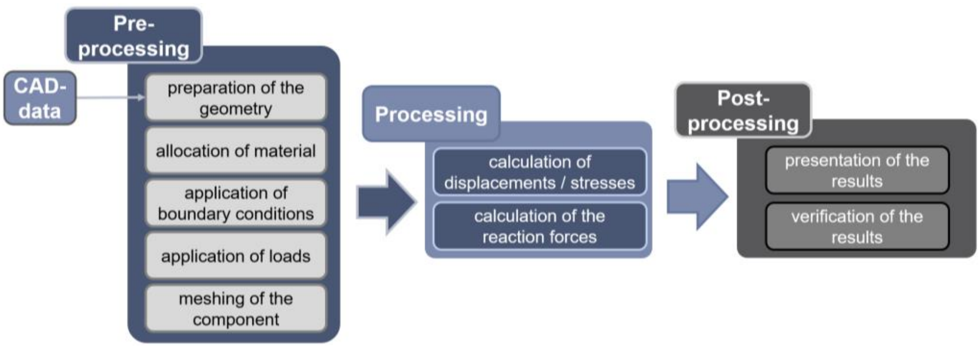

Figure 1. Simplified FE analysis process according to Vajna et al. (2018).

The simulation process is divided into three steps: Preprocessing, processing and postprocessing. The first step comprises the setup of the simulation, including the definition of loads and boundary conditions, as well as the material and the mesh quality. The created model is then calculated in the next step using the finite element method. In post-processing, the user evaluates the calculated results through various metrics which can be applied in different areas.

2.2.2. Knowledge-Based Support Tools

A large number of methods have been developed in recent years, all of which contribute to the employment of digital engineering in the FE-simulation cosmos. Based on the phases presented in the previous chapter, exemplary methods are presented in the following. These procedures all pursue the

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goal of improving or optimizing the respective step to improve the quality of the final simulation product or enable faster simulations.
In the first stage of the simulation process, the preprocessing, the method of Kestel et al. (2016) can be consulted. This approach uses a combination of text mining and ontologies to use existing knowledge about simulations in an automated way. Different text-based information sources can be used for the simulation build-up, like simulation reports or VDI guidelines. This knowledge can then be utilized in an application-sensitive manner, for example, to automatically map the degree of modelling of screw connections.

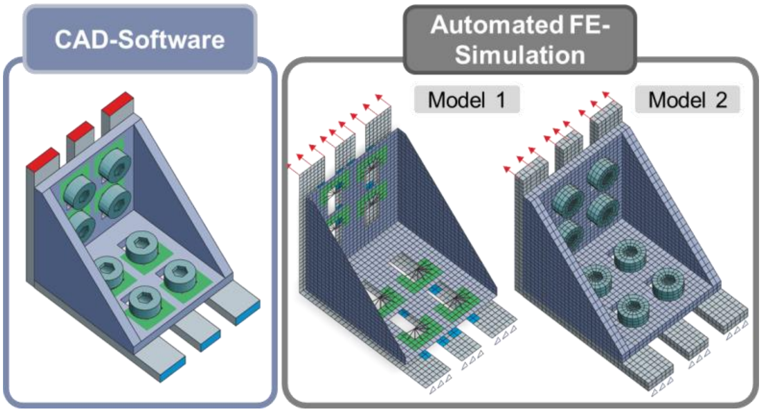

Figure 2. Example of displaying the different results of the method developed by Kestel et al. (2016)

An application example is shown in Figure 3. In this case, the first model can be used for simple estimate calculations and a quick design iteration. For this purpose, the model is automatically reduced to 2D elements and beams, which decreases the accuracy, but allows a significantly faster calculation. The second model, on the other hand, has a much higher level of detail and accordingly uses volume models and 3D elements, furthermore contact connections have been added to further optimize the simulation result.
Another approach developed by Sauer et al. (2018) supports the post-processing of FE-simulations. This approach substitutes new FE calculations for local areas of a component. Through a combination of Design of Experiment (DOE)-based parameter studies with a deep learning framework, a prediction can be made about product properties in local areas of a geometry. Especially for new manufacturing processes, this approach offers a lot of potentials, therefore the demonstrator was also developed for sheet-bulk-metal formed parts.
After examples for the application of digital engineering methods in the first two steps of the FE-simulation process have already been presented, a procedure for the last step of the simulation chain will be explained in the following. The procedure developed by Spruegel et al. (2021) involves checking simulations for plausibility. For this purpose, the simulation is transferred into matrices which provide the input for a deep learning network. Besides the examination of the results, the method is also able to consider the boundary conditions and the geometry as input.
All the methods presented here have in common that they are only employed in one specific simulation process step. Therefore, the goal of this publication is to establish a concept for combining different simulation process steps.

3. Concept for an Initial Design-Checker

As stated above, there are several tools for data-driven support of simulation tasks. Unfortunately, those tools are standalone expert tools and not easy to use for inexperienced users. In current development processes, simulation departments are process bottlenecks, since only a few specialists are able to perform and evaluate simulations. Typically, an adaption design process is structured as follows.

1. The design department creates a new design based on old design versions
2. The design is transferred to the simulation department; often an exchange format is needed

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3. The simulation is calculated and evaluated
4. The simulation specialist gives feedback to the designer, whether the design fulfils the requirements.

This process chain is iterated until all requirements are met. Our approach wants to frontload this process. When the designer changes parameters, he can open a web browser integrated into the CAD-System. In this Browser, a web app takes over the new parameter and performs an estimation of defined target values like stress or displacement. The designer gets feedback immediately. This is a huge benefit compared to an automated FE-Workflow, where the designer could trigger the simulation as well but has to wait for the results. Depending on the complexity of the simulation, this may take several hours. Of course, the simulation department is not replaced. The simulation engineer serves as a specialist and contact partner for questions and performs the final validation. The approach relieves the burden on the special department and enables more intensive work on critical problems. By performing the initial design-check before submitting the geometry to the simulation department, we predict higher geometry quality and thus reduced iterations and a faster time-to-market.

3.1. Concept Overview

In the following, we present a data-driven simulation toolchain to connect existing support solutions in a web-based simulation support tool for designers. The central goal of the approach is to enable designers to perform an initial check on newly developed geometries. Those checks are limited to standard load cases on known parametric geometries. By performing this initial design-check before submitting the geometry to the simulation department, we predict higher geometry quality and thus reduced iterations and a faster time-to-market. Figure 3 shows a further development of the simulation process chain shown in Figure 1. The whole idea is rooted on a real-time solution estimation, skipping the preprocessing and processing steps and generating a result immediately as shown with the green arrow pointing from CAD-data to postprocessing. In case of changed loads, the link is between the preprocessing, since loads are applied there, visualized by the dashed green line. Afterwards, the quality of the results is checked. If this is insufficient, an automatic recalculation based on the finite element method is carried out. With the simulation results, a subsequent plausibility check is performed.

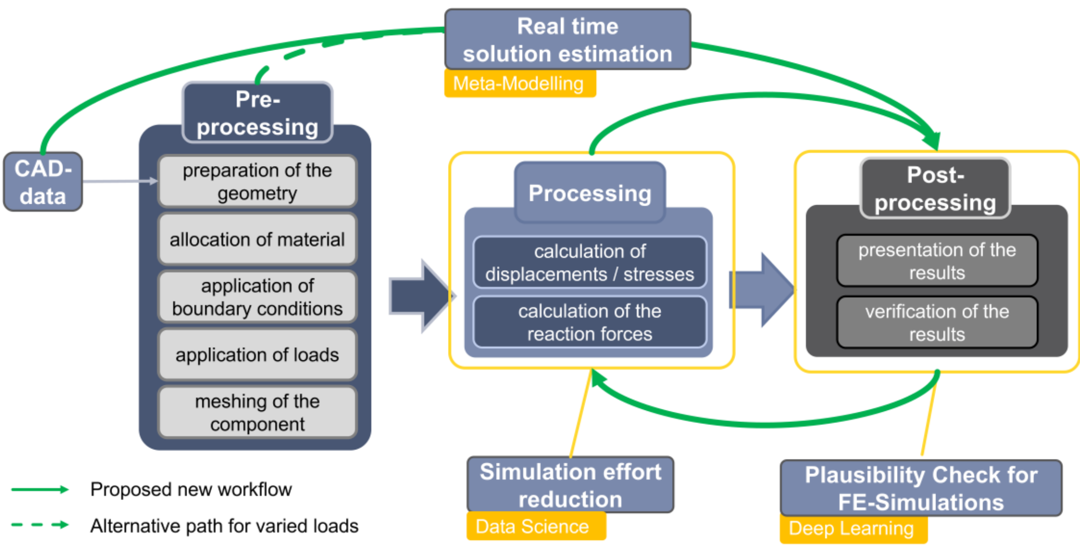

Figure 3. Adapted process chain to perform an initial Design-Check

The entire process chain is processed automatically. The user interacts with the system exclusively through a web interface. This has the advantage that inexperienced users do not need to be trained in the use of the FEM system, but only need to change input values that are relevant for them.

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After the overview of the overall idea, the implementation concept will be presented below before the relevant modules are explained in detail. Figure 4 visualizes the whole concept.

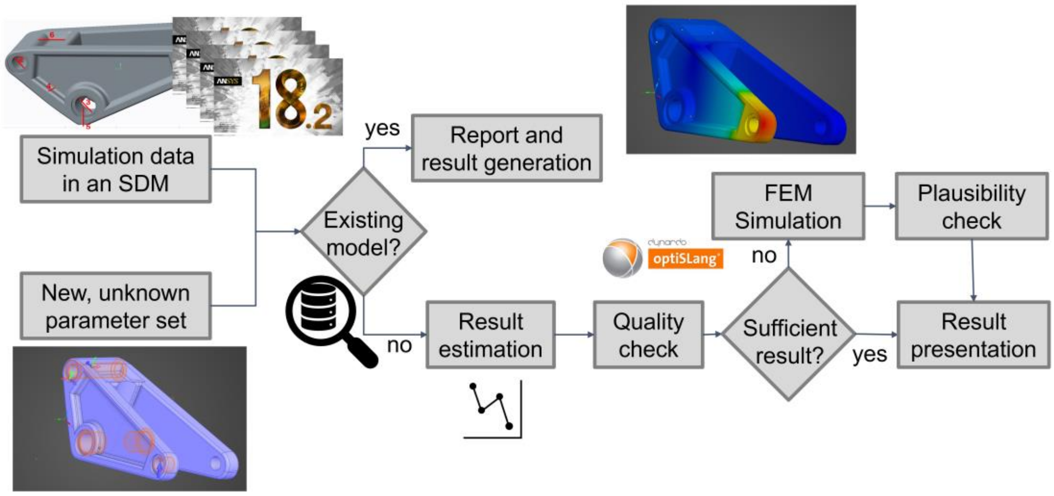

Figure 4. Concept for initial design-checks

The basis of the whole concept is a stock of simulation data, stored in a simulation-data-management system (SDM). In an industrial context, this SDM contains all simulations, performed in the company in the last years. A product designer, who is going to do an adaption design of a parametric model, now only enters the new parameter set into the system through a web interface. The SDM checks, whether this parameter set is present in the system and presents the result if there is one. In the case of no previous results, an automatic estimation is done. The first step of this evaluation is to perform a first real-time estimation of maximal stress and displacement based on the stored data. Alternatively, case-based reasoning methods could be used. Based on fitness factors, a result quality check is performed. If no sufficient estimation was detected, the system automatically performs an FE-simulation. Since designers, unexperienced in FEM evaluations, suffer in evaluating simulations in aspects like plausibility or criticality, a second level of support is added. This level adds functionality in checking the simulation plausibility based on a neural network, trained with data from a parameter study as well. This check gives the designer an insight if the simulation result is plausible and therefore resilient.

Even if the developer does not have the confidence to evaluate the results completely on his own, results are available at this stage that a simulation specialist can use to perform an expert evaluation without having to run a simulation himself.

The application of this system offers many potentials for the product development environment. Especially by estimating new simulation versions through metamodels, iterations for product revision can be shortened, which in turn leads to time and money savings. The whole concept also leads to a relief of the simulation engineers in standard tasks, because simple changes do not have to be recalculated and evaluated. The tasks for the different roles in product development are also changing. This is described by Bickel et al. (2019) in the way that simulation engineers can handle new tasks from the field of digital engineering. Their specific knowledge is irreplaceable for the application of these new methods as the goal is to transfer the existing know-how into these algorithms. The plausibility check supports the generation of more meaningful simulations and thus increases the quality of the results.

In the following sections, we take a deeper look at the two central modules, the real-time solution estimation and the plausibility check.

3.2. Demonstrator

After the detailed explanation and presentation of the new concept to combine methods of digital engineering for the improvement of the FE-simulation workflow, this chapter will describe the applied demonstrator. A part of a full-suspension mountain bike rear suspension serves as an exemplary

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model, based on the demonstrator in Spruegel et al. (2021). The selected part is a mountain bike rocker, which connects the damper to the rear swingarm. This structural element is commonly found on bicycles with the Horst Link damping principle, which offers off-road advantages due to its suspension travel. Unlike the standard spring setup, this design provides linear spring travel, which normally recreates a circular path. The basic shape of the mountain bike rocker can be observed in Figure 5.

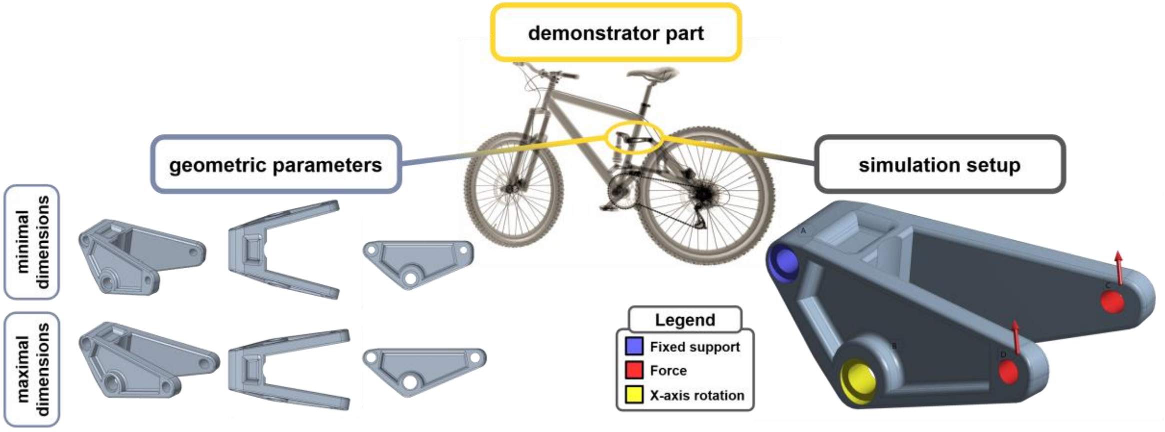

Figure 5. Overview of the mountain bike rocker including its geometric parameter and the layout of the FE-simulation.

In addition to the representation of the part, the boundary conditions for the simulation can also be seen in the image. The connection to the damper has been modelled in a simplified way as a fixed constraint, which is highlighted in blue in the graphic. The yellow area represents the axis of the rocker and is therefore only rotationally movable. The surfaces marked in red represent the force application areas, which simulate the load case in a simplified way. The simulation model is parameterized, where the constraints and the geometry can be varied. A total of eight geometry features of the rocker can be adjusted, starting with the different hole diameters, through the leg lengths and widths, to the angle of the two legs. In addition, the depth of the profile cut-out and the hole spacing on the frame side can be chosen freely. The fixed support and the rotational bearing cannot be altered, but the force vector can. This is parameterizable in the three coordinate directions and also in the type of load application. Two scenarios are distinguished here. On the one hand, the general load case is simulated by applying force to both holes. There is also another, worst-case load scenario. In this case, the entire force is applied to only one leg of the rocker. This extreme load case could occur, for example, in the case of a missing bolted connection or a heavily worn axle connection, whereby the force is completely transferred to one leg. The last available parameter is the meshing of the component, which is choosable by the mesh element size.

This simulation setup is the basis to demonstrate the concept presented in chapter 3. On the one hand, a new approach is presented to show how new simulations can be avoided by substituting them with metamodels, and on the other hand, a model is developed to evaluate FE-simulations according to their plausibility by applying Deep Learning.

3.3. Real-Time Solution Estimation

The central goal of the simulation effort reduction is to reuse existing simulation data, to reduce the performed simulations and therefore minimize iterations between simulation and design department. The method provides a first result estimation based on existing simulation results. This check is performed by the designer. Therefore, a first evaluation is done, reducing iterations and development times. The whole method is inspired by the findings of Sauer et al. (2018) and the idea of local metamodels to predict product characteristics.

The method is based on simulation data of previous development cycles. To estimate the results, the new set of parameters is given to the metamodel, which calculates the maximal stress and displacement. Depending on the metamodel fitness factors coefficient of prognosis (CoP) and absolute

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error (MAE), a decision is automatically made as to whether the quality of the forecast is sufficient for an initial assessment. To realize the result estimation method for the given demonstrator, a setup in the tool ANSYS Optislang was built as visualized in figure 6. The method is based on simulation data of previous development cycles. At first, a database has to be generated via a parameter study, which serves as the basis for the metamodel. This is done in the block "database" on the left side. A parameter study was calculated for a total of 5.000 design points sampled by an advanced latin hypercube sampling. Since only maximal displacement, maximal stress and the individual parameters are needed, only those were saved for later use. This database was used to train a metamodel of prognosis in the block on the right side of the "database" block. The system generated three regression metamodels, based on second-order polynomials, moving least squares method and kriging. Based on the CoP and RMSE values, the best model - second-order polynomials - is chosen for the final model. Other models like deep feed-forward networks are possible too but are not taken into account for now. To increase the estimation accuracy, the input data is reduced to relevant parameters. The identification of those parameters is done through a sensitivity analysis. The parameter reduction removed the parameters for the diameters and the hole spacing on the frame side.

To estimate the results, the new set of parameters is given to the metamodel, which calculates the maximal stress and displacement. This is done in the "estimation" block. In this block, the parameters for the new evaluation are set and given to the metamodel. After the calculation, the quality check is done in the subsequent python block. Depending on the metamodel fitness factors coefficient of prognosis (CoP) and absolute error (MAE), a decision is automatically made as to whether the quality of the forecast is sufficient for an initial assessment. For example, the proportion of the absolute error of displacement ($disp_{err}$) compared to the estimated displacement ($disp$) can be calculated.

$$\frac{disp_{err}}{disp} * 100\% < 5\%$$

Additionally, the local CoP, given by the metamodel is compared with the limit value of 90%. Doing this, we can realize the "reliable check" stated in the intial research question. If one of the four checks returns a "true" value, signalizing the ratio being greater than 5% or the cop smaller than 90%, the re-evaluation block is triggered. In this block, the new parameters are given to an Ansys Workbench block, performing a full FEM-Simulation and returning the calculated maximal displacement and stress. The last block performs a comparison between the calculated and predicted values. This shows that the predicted values are on average 1-2% larger than the calculated values.

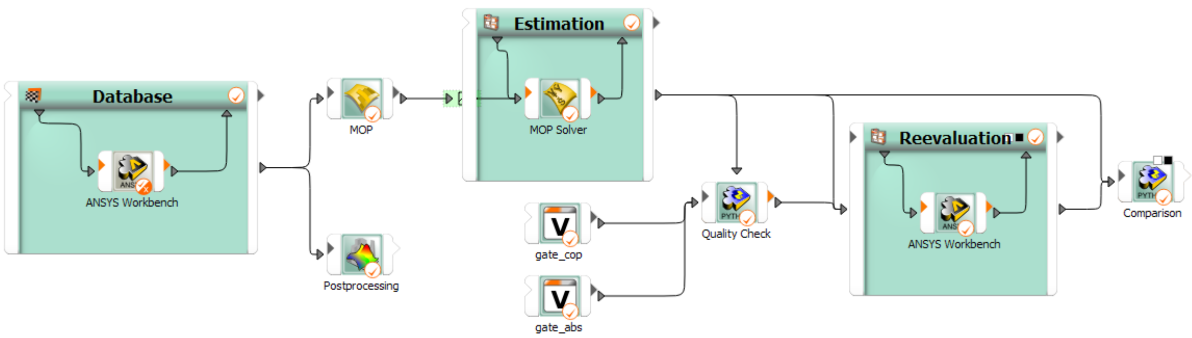

Figure 6. Ansys OptiSlang setup

3.4. Plausibility Check

The idea of plausibility checks is rooted in applying FE-simulation by novice or less experienced users. The method is intended to provide an automated check of the simulation to estimate whether the results and input data are generally plausible. In this context, the term plausible has been described by Spruegel et al. (2015) and means that a simulation does not contain major errors that an experienced simulation engineer would recognize, for example incorrect force conditions or mesh parameters.

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The problem with transferring FE simulation to Machine Learning methods is the informality of the input data. FE-simulations are based on volume meshes, which, depending on the geometry and meshing parameters, can vary in size, resolution and complexity. On the other hand, Machine Learning methods always require a uniform input for the respective algorithm; therefore, data preparation is necessary before handling the data to the models. Spruegel et al. (2018) developed a method for projecting points onto a detector sphere to convert the simulation results into a matrix. This procedure projects points from the centre of the volume mesh onto a sphere, which is divided into pixels. Afterwards, the values per pixel can be evaluated and unfolded to a matrix-like world map. This transformation is not only applied to the results of the simulation but can also be used to represent the boundary conditions such as forces, bearings and meshing. The combination of simulation layout and results can thus be created into a vector for one simulation. This unified vector subsequently serves as input to the Machine Learning algorithm.

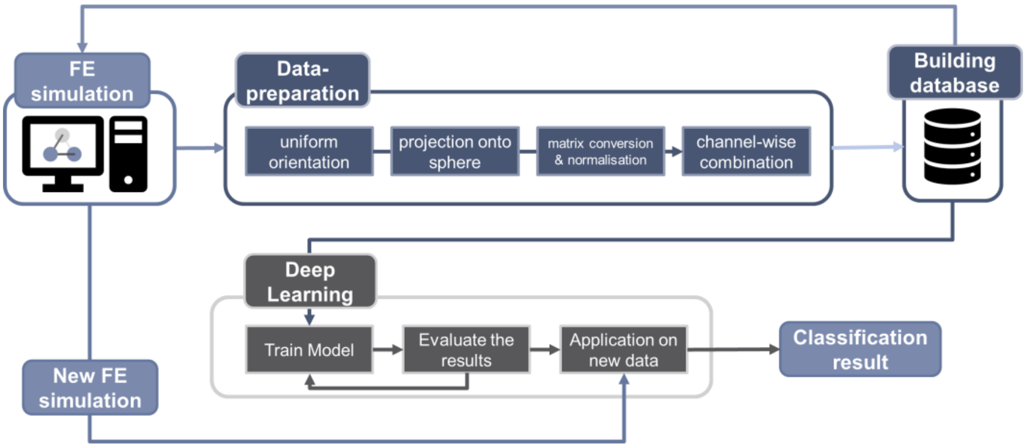

Figure 7. Overview of the plausibility check procedure for FE-simulations

With this method, it is possible to build up a large database of FE simulations and to divide this automatically into classes. The overall procedure is shown in Figure 7. In addition to data conversion, labelling of existing or calculated simulations is also an essential task. This can only be performed by experienced simulation engineers since the correct label for a simulation is crucial for a good classification.

Previously, this method was only applied to different components, but the effects of changing load cases were not investigated. For this reason, a new deep learning architecture should now enable the network to distinguish between different load cases and thus determine the plausibility of a simulation result reliably. The exact procedure and the corresponding data set will be explained in the following based on the demonstrator.

In order to test the plausibility check method, a database must first be generated via a parameter study. For this purpose, a d-optimal experimental design was calculated for a total of 11.997 design points and the utilization of all possible parameters. The total amount of data generated is about 800 GB of simulation data. Whereas the processed data for training the Deep Learning Model only requires 1,85 GB of storage space. In total, 26 matrices are generated per simulation, which represents the geometry, boundary conditions and results. After the initial calculation and labelling of the data for the first section of the parameter study, it was noticed that the number of non-plausible results was very high, so a new DOE was created again with more plausible results. For this study, data labelling was performed by the researchers of this paper. The objective was to achieve an almost even distribution of plausible to non-plausible results so that the evaluation over the overall accuracy remains meaningful and the training of the deep learning models performs better. In total, the dataset contains 5.969 non-plausible and 6.028 plausible simulation results. For the evaluation of the results, the data were randomly divided into test and training data with a ratio of 20/80. The training data has subsequently been split into training and validation data, with 10% being used as validation data during training.

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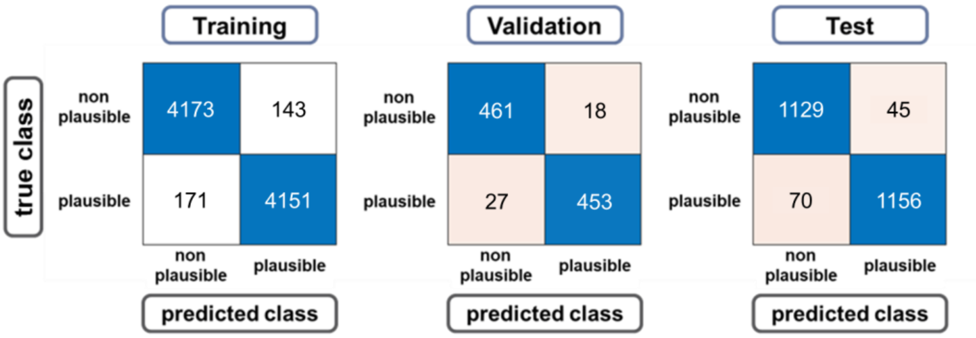

Figure 8. Different accuracies for the demonstrator part

The Deep Learning Model is an adapted vgg16 which uses the sevral layers of convolution and pooling for the classification. The special characteristic of this configuration is the adaptation to 26 channels since most CNNs are designed for RGB images and thus 3 channels.
The results are displayed in Figure 8. The precise classification accuracies are: Training 96.36 %, Validation 95.31 % and Test 95.21 %. These results show that the task of rating simulations with different load cases based on their plausibility could be fulfilled.
Therefore, this procedure should provide enough support for the user to be able to give an estimation of the plausibility of a simulation in case of a possible recalculation of a simulation.

3.5. User Interaction

In the current development state, the designer could use the tool as followed. At first, the new parameters are set in the "estimation"-block of the OptiSlang project. The result of the stress and displacement estimation, and the assessment of whether a re-evaluation should be carried out or not, is printed on the integrated console. Afterwards, the re-evaluation is performed. During this step, the needed data for the subsequent plausibility check is generated and saved. Afterwards, the designer has to execute the plausibility check manually. Based on the estimated result and in some cases the exact result and plausibility checks, the designer receives initial feedback as to whether the current development status is promising.

4. Discussion

The system's application with the demonstrator clearly shows that the different modules work and can deliver significant benefits. However, the concept still has drawbacks in its current state. The general application of the system is not easily transferable but limited to one part and a variation in the load case, so it is aimed at companies that specialize in one part. To transform the system to a new part, the individual database has to be evaluated. If companies have old simulation data, the system can be easily transformed. Wheather no calculated data is available, the generation will need significant effort. Furthermore, it should be noted that the demonstrator is a scientific example and does not derive directly from a company; therefore, to verify the methods, a demonstrator should be carried out again in collaboration with an actual enterprise. Also, the system does not work entirely autonomously since interventions of people are still necessary. However, this step has been chosen intentionally so that experienced engineers can intervene in the system and recognize possible false estimations. A further overall advantage is that this concept enables components to be tested at an earlier stage, which in turn saves costs. This is mainly because inexperienced users are given access to FE-simulation results and can consequently check the product at an earlier stage.
In summary, the presented method offers many potentials in the application, but it is also only suitable for specific simulations boundaries.

5. Conclusion

In our contribution, we have shown the power of data to support designers in performing a first initial check on new designs without the need of iterating with the simulation department. Additionally, we presented an integrated process chain, to enable a seamless development process. Overall this reduces

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the workload in the simulation departments due to fewer iterations needed. This enables those experts to invest more time in critical problems. We want to emphasise that this method is not intended to replace simulation departments but to relieve them. Future work will deal with further linking of the above methods. Among other things, various prediction possibilities are being tested. In addition, we are investigating whether plausibility checks can already be applied to the initial result predictions. In addition, an extension of the method to a percentage score of plausibility for the FE result could be elaborated, which would extend the current class categorization.

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