Mathematical Optimization of Clamping Processes in Car-Body Production

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Abstract

Up to now, the process of adjusting clamping devices in car body manufacturing has been driven by expertise; it has been repeated in costly iterations until the necessary quality has been achieved. Absent appropriate methods, even the high-performance numerical representations of this process have only been able to support this process to a limited extent. This paper outlines a method to assist the adjustment activities carried out on machinery based on numerically represented model functions, which will subsequently improve the usability of FE simulations during the machinery ramp-up.

Keywords: Finite Element Method (FEM), Clamping, Aluminium, Measurement, Sensitivity Analysis, Optimization, Process Chain

1 Introduction

The process of car body manufacturing is subdivided into the steps of sheet metal forming, assembly, mounting and paint drying. In general, car body production planning relies on a wide variety of FE tools that make it possible to predict the response of sheet metal parts and assemblies in a numerical manner. Especially in recent years, experts have made advances in the process chain in the fields of clamping, joining, seaming and in heat treatment [1] [2] [3] [4]. However, it was not possible to guarantee the dimensional accuracy of the stampings in every case. The springback response of advanced lightweight design materials, such as aluminium and higher strength steels, is complicated to be deal with in process [5], which, in turn, results in a number of time-consuming and expensive die adaptations in the ramp-up process. One strategy to obtain prototype car bodies in the ramp-up process whose dimensions are within the required tolerances consists in trying to compensate for dimensional deviations of the individual parts in the subsequent assembly process. In this approach, targeted localization and gripping of individual parts makes it possible to affect dimensional accuracy in areas that are relevant for quality and thus to maintain the resulting manufacturing tolerances by means of the follow-up joining operation. This was demonstrated in projects

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and studies by Eckert [2], Hu [6], Liao [7] and Matuszyk [8]. However, the ability to achieve a high quality representation of the clamping process only indirectly improves the adjustment measures, which still have to be executed repeatedly by highly qualified experts and be checked for success. For this reason, the goal is to use the potential of the numerical prediction later on in order to define optimal adjustment activities in an automated manner, without the need for comprehensive expertise and in a limited number of test runs. This publication's content is aimed at investigating the representation of deformations in the clamping procedure in a meta-model, as well model optimization following the Functional Build approach (FBA)

2 State of the Art

2.1 Clamping device design

The design of clamping devices for car body manufacturing always follows analogous principles (see Fig. 1).

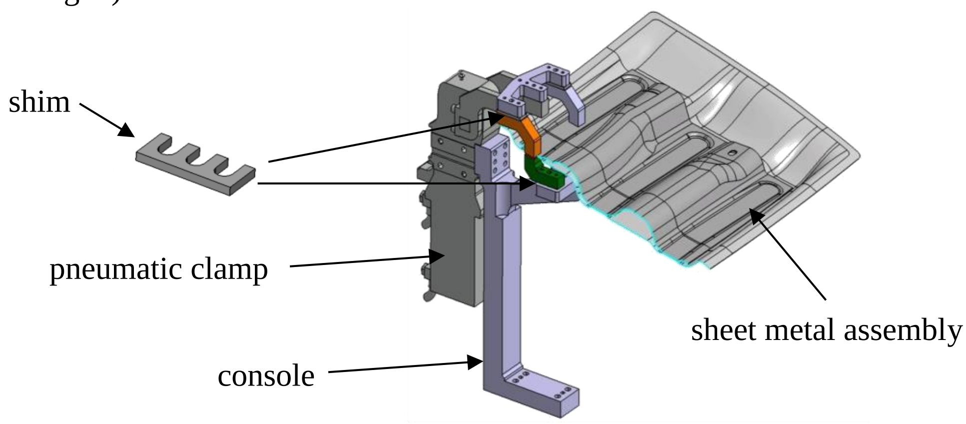


Figure 1: clamping device

Design is based on consoles to be mounted to a bottom plate. The consoles give access to joining tongs and grippers and allow contour blocks and clamps to be attached. When closed, the assembly is fixed between active and passive surfaces. To connect the contour blocks with the clamping unit and console, a so-called shim (derived from the verb “shimming“) is utilised. The industry standard for the minimal adjustment increment of these shims is 0.1mm.

2.2 Numerical representation of the clamping process

Eckert [2] shows that it is possible to numerically represent the influence of the clamping process' dimensional accuracy with sufficient precision by modelling the active clamping surfaces using the simulation software ESI PAM-STAMP 2G (ESI Group). Based on these results, Drossel [1] verified that the clamping process can be represented very well even in regions that are highly deformed due to clamping when using the precise geometry of the active surfaces. As demonstrated by an industrial application for a cut-out of a passenger car's side panel frame in Landgrebe [9], a numerical forecast of dimensional accuracy for a manually defined clamping position has already simplified process planning for car body manufacturing; with the help of this development is was possible to replace costly trials in practice.

2.3 Sensitivity and optimization

Figure 2 provides an overview of how to subdivide numerical parameter optimization into three essential subdomains: sensitivity analysis, regression analysis to generate a meta-model and parameter optimization.

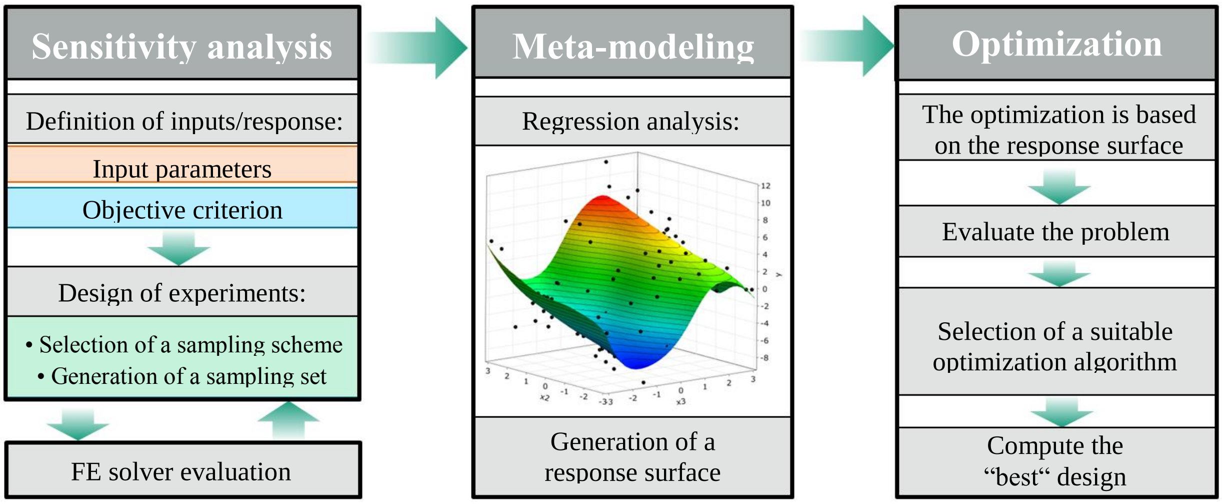


Figure 2: Flowchart of numerical parameter optimization

In the first step, sensitivity analysis is employed and the input parameters are deliberately varied, thereby creating a point cloud in the parameter space (Fig. 2, left). The goal is to determine the impact of the controllable input variables on the defined command variables in a minimum number of trials in an optimal manner. In the next step, a meta-model is approximated by means of the samples generated (Fig. 2, middle column). Based on the meta-model, an optimization algorithm is applied to the parameter space and searches for an optimal problem solution (Fig. 2, right) [10] [11].

Following Will [12] random-based sampling strategies based on the Monte Carlo method (MCS technique) should first be used to define the data points that are necessary for the model function. Since, in particular in the case of small sample sets, the application of the Monte Carlo method results in undesirable input correlations among the input parameters, the Latin Hypercube Sampling (LHS technique), a refined method [10] [11] enabling better distribution of the samples in the test space, could provide a solution. As investigations have indicated, the input correlations can be significantly reduced with this method [10] [13]. However, the LHS technique according to Siebertz [14] does not guarantee a test space that is completely free of correlations when there are only a few data points. For this reason, Huntigton [15] introduced the Advanced Latin Hypercube Sampling (ALHS technique). Applying this method, the input correlations can be reduced to a minimum after only a few data points are removed from the parameter space. Another stochastic paradigm, called the Boundary and Best Neighbour Sampling (BBNS technique), is described by Wang [16]. In contrast to the other design experiments, the data points are only generated in the region of a potential peak value, so that one can work without factor adjustment and the effort necessary for numerical calculations can be diminished.

After sensitivity analysis, the parameters are optimized based on the meta-model generated. The optimization algorithm is applied to minimise the objective under predefined secondary conditions and to determine the optimal design [12]. Based on an earlier preselection, the existing paper is aimed at elucidating the following optimization algorithms:

- Gradient based algorithms
- Evolutionary algorithms
- Adaptive Response Surface Methodology

2.3.1 Gradient based optimization

The paradigm for parameter optimization by means of gradient information is to achieve optimal design from a given poor design through the quickest possible deduction. Will [12] shows that the numerical gradient techniques are characterised by high requirements in terms of the meta-model quality. According to Will [12], the most critical issue is that the gradients are unusable if a problem is not differentiable or in the case of numerical model inaccuracies or local extremes. Nevertheless, the category of gradient optimization techniques is the best of all the algorithms in terms of convergence.

2.3.2 Evolutionary algorithm (EA)

Evolutionary algorithms are stochastic search techniques that follow the nature of biological evolution. Their basic idea is to create an artificial group of individuals that approximates the optimal design step by step [17]. An advantage of the evolutionary search strategy is that the design space is searched in a wide-ranging manner. Thus, potential local extremes are bypassed due to the high quantity of individuals created. Another advantage is that the evolutionary algorithms are particularly useful to solve problems in which a gradient analysis is impossible, such as in the case of discontinuous input variables. In comparison to gradient-based algorithms, however, the stochastic search techniques are characterised by a significantly poorer convergence response in the region of an optimum [12].

2.3.3 Adaptive Response Surface Methodology (ARSM)

When following the Adaptive Response Surface Methodology, the design space is locally approximated based on selected data points. To do this in each iteration, a sub-parameter space is created in the parameter space by means of a data point pattern. In this process, the limits of these locally approximated response surfaces should be shifted or zoomed as long as the global optimum is approximately found in the last iteration [18]. One consideration when using the ARS methodology is that no sensitivity analysis is feasible since the regression models change sequentially [10].

3 CAE-based numerical optimization of a clamping process

Since the clamping process of car body parts has hitherto been based on a series of changes driven by expertise, it should be supported by methods for the CAE-based optimization. For

this reason, an interface between the PAM-STAMP 2G (ESI Group) CAE software and the optiSLang (Dynardo) optimization software was engineered.
The PAM-STAMP 2G simulation program executes the numerical calculation of the clamping process based on a simulation model working with set parameters. Use of the optiSLang optimization tool makes it possible to analyse the sensitivities of the clamping control variables, and, afterwards, to optimize the corresponding parameters for them. Figure 2 shows a flowchart elucidating the process integration of the numerical clamping process in optiSLang.

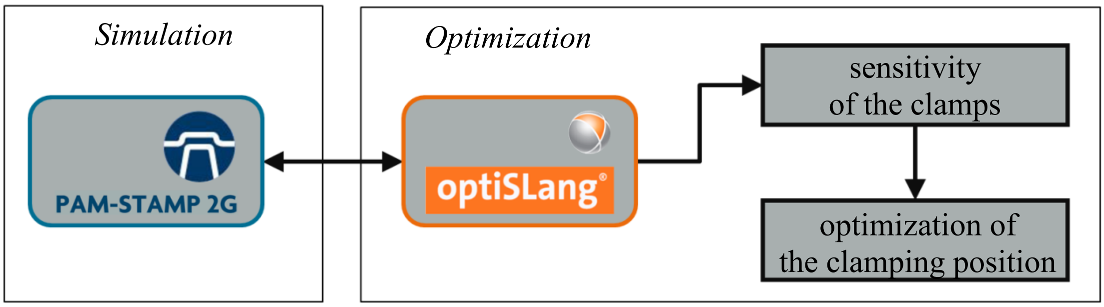


Figure 3: Integration of optiSLang into the numerical clamping process

3.1 Methods to determine clamping process sensitivity

Since the quantity of solver calls required is essential to the simulation time, it is first necessary to select a suitable experiment design for an efficient determination of sensitivities. The pros and the cons of the experiment designs introduced in the State of the Art to determine the sensitivity of clamping processes are compared in Figure 3 below.

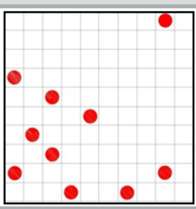
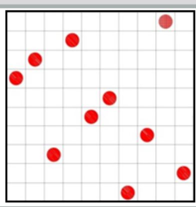
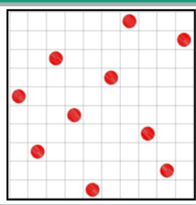
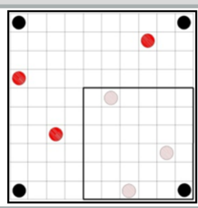
	Monte Carlo Simulation	Latin Hypercube Sampling	Advanced Latin Hypercube Sampling	Boundary and Best Neighbor Sampling
Sampling scheme:				
Number of samples:	High	Small	Small	Small
Advantage:		• reduced correlation • small number of samples	• no correlation • small number of samples	• small number of samples
Disadvantage	• strong input correlation	• low input correlation possible		• strong input correlation • risk of local extrema

Figure 4: Evaluation of stochastic sampling schemes

As can be derived from Fig. 3, when using Advanced Latin Hypercube Sampling, relatively few samples are required to generate significant meta-models, on the one hand. On the other hand, it is possible to cut the undesired input correlations of the input parameter down to minimum. Consequently, the ALHS technique is applied to analyse the sensitivities in the determination of the sensitivities.

3.2 Clamping process optimization methods

When selecting an appropriate optimization algorithm to search for a suitable clamping operation in the meta-model to optimize dimensional accuracy, the highest quality of results is achieved by means of the gradient optimizing technique **NLPQL**. Of all the techniques used, this algorithm is characterised by the best convergence response in the region of an extreme. If the gradient-based paradigm does not offer a result, then, as an alternative, the evolutionary algorithm can also be applied to enhance design, since it is very robust in terms of the noisy response surfaces and local minima. In contrast, the Adaptive Response Surface technique is not suitable to solve the problem that appears, since there are no meta-models available in the design space which could be taken as a basis for ongoing optimization runs due to a sequential search for potential extremes. As a result, the samples have to be completely recalculated for each optimization using the CAE program. This is far more time-consuming than the meta-model optimization.

4 Validation of the proposed methodology

4.1 Setup for the optimization

The car body assembly and clamping device by *Eckert* [2] is used in order to test and validate the proposed methodology of the meta-model based optimization of clamping processes. It combines several characteristics of add-on-body parts, such as surfacing, form elements, contact surfaces and flanges. The assembly is similar to a bonnet geometry and consists of an inner part (grey) and a reinforcement part (green) (see also Fig. 5).

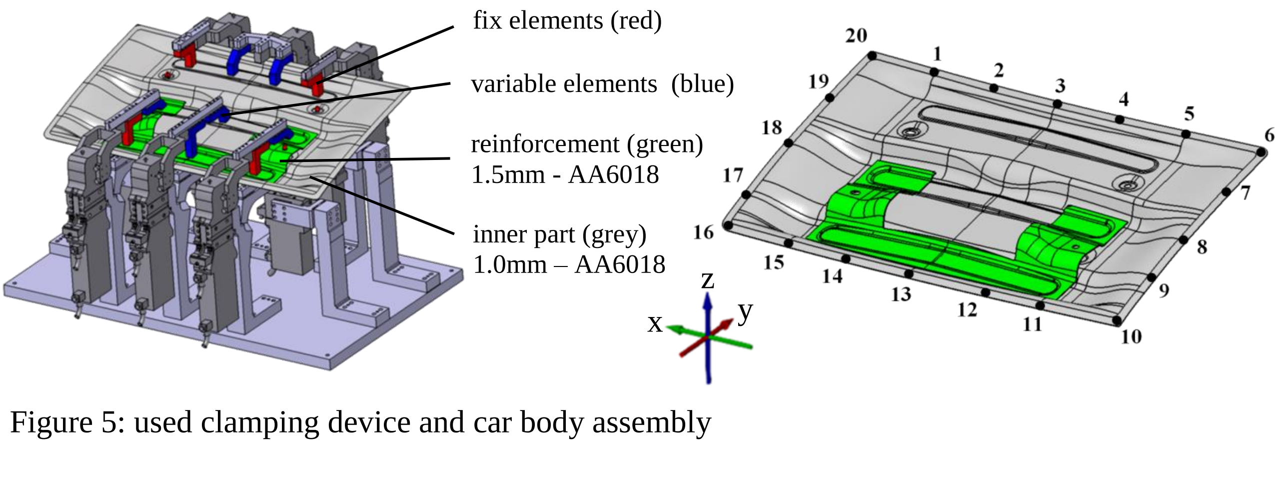


Figure 5: used clamping device and car body assembly

4.2 Input parameters

As shown in Figure 5, the components of the assembly are mutually localised and clamped by means of the blue and red coloured clamping points. The four clamping points marked in red are fixed in their position, so that the results of the simulation and the CAD file can be compared. The clamping points marked in blue can be variably adjusted in Z orientation and are thus used as input parameters for parameter optimization. Since the minimal adjustment increment is 0,1mm for the variable clamping points (blue) due to the shims used (ref. Fig. 1), six variable clamping points arise for the existing assembly. They can be adjusted in the interval from -2.5 mm to 2.5 mm (50 positioning options per clamping). For the existing case of application, a combination of approximately 17.6 billion positioning actions exists.

4.3 Objective definition

Dimensional accuracy is evaluated via 20 discrete measuring points that output the distance between the simulation model (real values) and the CAD file (nominal values) (see Fig. 6). These measuring points are defined according to the Functional-Build approach in the quality-relevant connecting areas of the car body structure. To define the optimal controlling measure, afterwards, an objective is specified. In the objective, all approximated representation models are summarised to one function. It is aimed at adjusting the variable clamping points within their defined limits of +-2.5 mm in a way that the range of tolerance marked green is maintained with a tolerance of 0.5 mm for all measuring points due to the intentional mutual clamping of the components (demonstrated by the distribution of measuring points in Fig. 7).
For efficient design of experiments, a meta-model with 100 data points was generated by means of ALHS. The NLPQL technique is employed as optimization method to search for an optimal clamping adjustment.
In the practical design of clamping devices, one of the main issues is accessibility for joining tongs. Here, a loss of rigidity is inevitable. As a result, the active force when the clamps close (320Nm/clamping) causes the device to be deformed by 0.5 mm maximum in the case of major adjustments (see Fig. 6). Since the expected methods to integrate structural stiffness into assembly simulation are still under development, a force of 700N per clamping point was defined as the truncation criterion. Based on this information, optimization algorithms based on a Pareto front can be applied to truncation criteria for adjustment activities when exceeding a user-defined force.

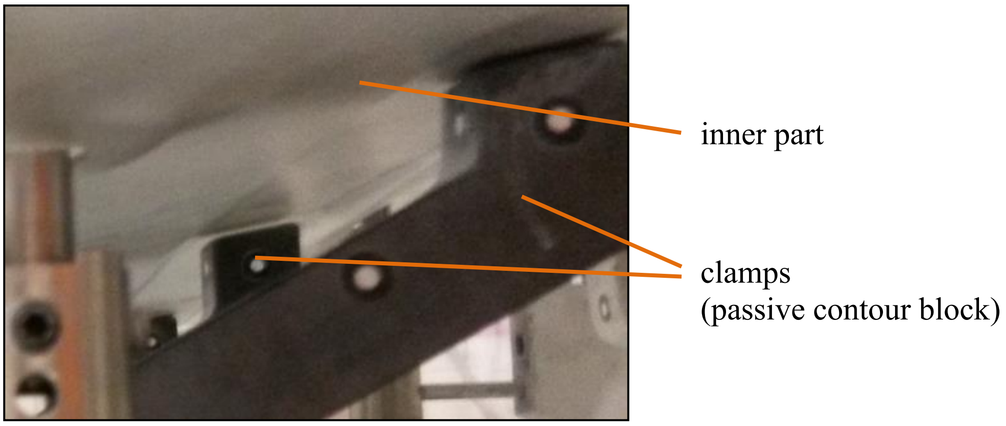


Figure 6: used clamping device and car body assembly

4.4 Optimization results

Fig. 7 shows the result of the new meta-model paradigm for the optimization of clamping procedures. The green zone defines the tolerance of the shown assembly's dimensional accuracy. It can be seen that the assembly in the original clamping state (CAD-0) – before optimizing – clearly exceeds this tolerance value at measuring point No. 10

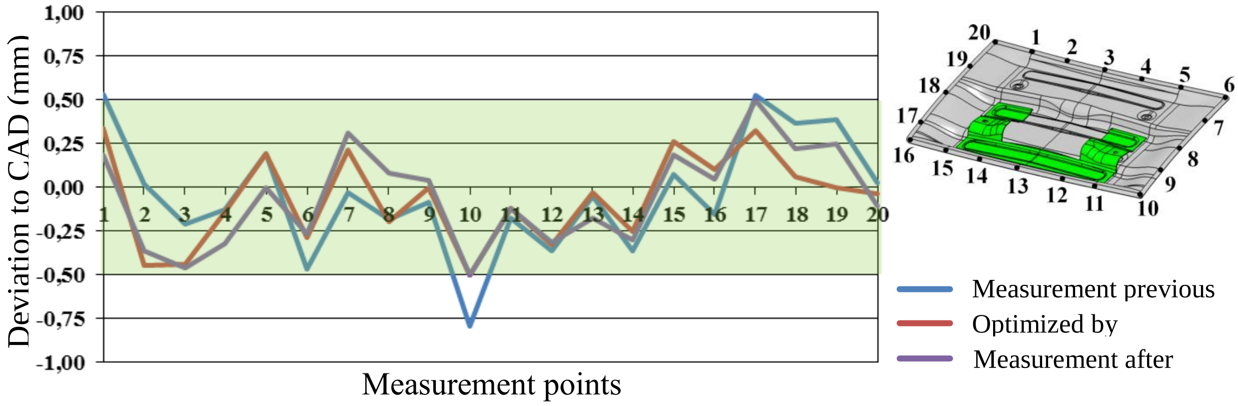


Figure 7: used clamping device and car body assembly

A result capable of improving the tolerance compliance of the measuring point was found by means of an optimization function based on a generated meta-model. The values illustrated in red represent the assembly whose dimensional accuracy has been optimized by means of an FE algorithm, whereas the actual measured values are shown in magenta. It can be determined that the authors succeeded in bringing the assembly into the tolerance range required thanks to the optimization measure. This finding also indicates that the difference between the measuring values predicted mathematically and the values achieved in reality amounts to a mere 0,2mm. Despite the assumptions mentioned, this result implies that the quality of the prediction can be accepted as sufficiently accurate to simplify the structural stiffness representation.

5 Summary

The investigation indicates that clamping processes can be represented at sufficient accuracy by means of mathematical functions. It was demonstrated that optimization runs are feasible in terms of special criteria or the objectives sought. Thus, the authors created a basis to support adjustment activities in car body manufacturing systems by numerical calculation of variants and subsequent comparison of variants.
The adjustment activities provided by the optimization program were constrained by the limits of the clamping element's force and stiffness, defined manually. In the subsequent studies, unexplored issues arose in terms of the process sensitivity, which has not yet been researched in terms of the deformation of the clamping structure. Another open issue is the conscious deformation of the clamping structure as an optimization option. As a step into this direction, force and stiffness should be implemented.

6 Literature

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