Data-Based Prediction Model for an Efficient Matching Process in the Body Shop

Arndt Birkert, Johannes Weber, Moritz Nowack, Christian Schwarz, Benjamin Hartmann, and Philipp Zimmermann

Abstract Achieving the optimal dimensional quality for automotive body parts today is a time and cost-intensive process still often based on trial-and-error approaches. There are two ways to improve the accuracy in the production process: Early modification of the tools in the press shop is one way to significantly manipulate the dimensional quality of parts, although resulting in high costs. The other—much more time and cost-effective—way is trying to change the geometry in the body shop, although providing a lesser adjustment range. Definition of a reasonable parameter adjustment in a single joining stage needs expert knowledge because the adjustment of a single fixture component can have a complex impact on the final assembly. In this publication, a new approach based on finite element simulation and statistical methods is presented being able to characterize the interactions between clamp settings and assembly geometry and to identify the main impact factors on the dimensional accuracy of assembled body parts. The surrogate model is based on smart data, gathered from FEM simulations.

Keywords Body manufacturing process · Body shop · Body-in-white · Matching process · Assembly simulation · Smart data · Coupled process analysis · CPA · Machine learning · FEM simulation

Introduction

Considering the customers' increasing expectations of vehicle quality in terms of design, appearance, and functionality, the manufacture of dimensionally accurate and robust car bodies represents a fundamental aspect of automotive production. Typically, even slight variations in gaps between body assemblies, such as side panel

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frames and doors, can have a significant impact on the visual appearance of a vehicle. Throughout the body manufacturing process, many process influences affect the quality of the body assemblies (e.g. geometry variations of the individual parts) potentially resulting, in the geometry lie far outside the required tolerances [1]. This means that the ramp-up phase until the start of production (SOP) is characterized by time-consuming and cost-intensive adjustment loops. The shortening of these trial and error processes is an essential criterion for achieving competitive advantages in automotive manufacturing.

To achieve the highest possible degree of process capability, the numerical validation of individual process steps in car body production based on the finite element method (FEM) is part of the industrial standard [2]. The springback and gravity simulations performed are the prerequisite that enables a valid analysis of the dimensional quality of individual parts and assemblies at an early stage of development. In the automotive production process, the application of simulation methods based on the finite elements has been state of the art since decades [3]. The simulation results can then be used during the planning phase as well as at the start of the series production process in order to save time-consuming and cost-intensive quality loops [2]. Frequently used simulation engines are the commercial packages *AutoForm*, *PAM-STAMP*, *ANSYS*, or *LS-DYNA*.

Due to the large number of adjustment options along the automotive process chain, the identification of complex interactions based on trial and error approaches is not very target-oriented, so simulation is increasingly supplemented by parameter studies. Especially in the field of sheet metal forming and assembly simulation, Machine Learning (ML) methods are used to predict and optimize the effects of undesired process variations on the quality of parts and assemblies [4].

Through the integration of statistical methods into the virtual production process, it is possible to perform systematic variant calculations in the form of parameter studies. In automotive industry, studies are frequently employed to support, among others, the following tasks:

- springback compensation in sheet metal forming [5–7].
- robustness evaluation and optimization of the manufacturability of drawn parts during deep drawing to identify critical areas [8].
- optimization of the dimensional accuracy of assemblies [9].
- 3D representation of statistical measures on the surface of discretized scan or FE meshes by data reduction methods [10–12].
- identification of typical hemming defects [13, 14].
- sensitivity analysis to identify quality-relevant process parameters along the automotive process chain [11, 15].

An important approach for systematic use of parameter studies in the automotive environment is the method called Coupled Process Analysis (CPA) presented in [15]. The main advantage is the shape-based (elementwise) visualization of statistical quantities on the surface of FE and scan meshes in sheet metal forming and assembly processes. The procedure is shown in Fig. 1.

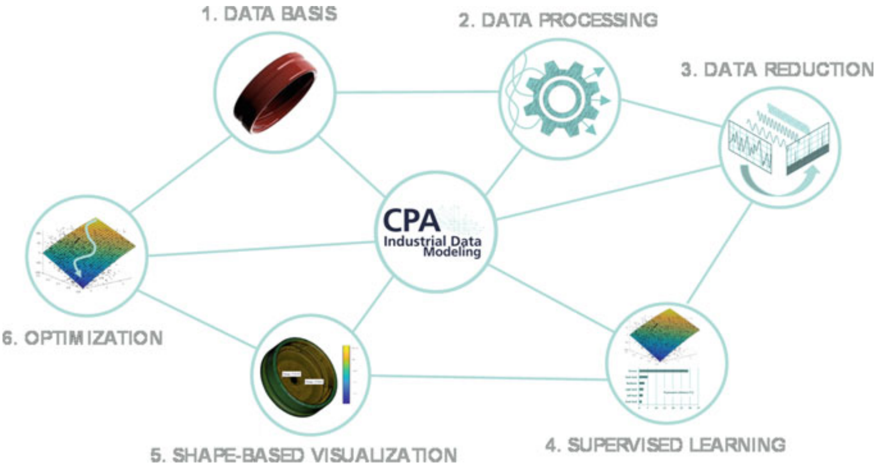


Fig. 1 CPA algorithm [15]

The method can be divided into five steps: In the first step, simulation variants are calculated by varying defined input parameters (e.g., variations of clamp and pin positions in fixture). The second step is to standardize the inconsistent simulation data. In the next step, the mesh-based simulation results (deviations from CAD target) are transformed into a low-dimensional feature space. The idea is a feature map of large data sets into a new coordinate system so that the input data can be described using a small number of geometric error modes. In the fourth step, surrogate modeling is performed in the low-dimensional feature space. Here, the input parameters are functionally linked with the error modes by linear and quadratic regression models. The models can also be used to estimate the sensitivities of the parameters in the feature space by variance-based methods. Through the possibility of inverting the feature mapping, a functional connection can be made between the surrogate models and the real space domain. This connection enables the shape-based visualization of sensitivities on the part geometry (step 5) and the optimization of the input parameters in the sixth step.

From these observations, it can be concluded that it is highly relevant to study how FE simulations and machine learning methods can be integrated more tightly, in particular, to find process-relevant parameters, which influence the dimensional quality of parts and assemblies. Therefore, within the present publication, a concept is presented that allows the identification of relevant process parameters affecting the dimensional accuracy of assemblies based on FEM simulations. The CPA algorithm presented in [15] is used for the statistical analysis of the correlations.

Overview of the Developed Concept

The developed concept is presented in the following with the corresponding workflow shown in Fig. 2.

1. Forming simulation with *AutoForm*

   The scatter of springback of the stamped part is strongly influenced by the variation of the sheet thickness, by the process forces of the press (e.g. blankholder force), the blank position in the die, the friction and material properties (yield stress and anisotropy of the material) [1]. Therefore, in a first step, the geometric variations of body parts are obtained by simulating the stamping process with varying parameters in *AutoForm*. The individual parts (subject to springback) are used as input data for the subsequent assembly simulations done with *ANSYS*. The idea is to take the individual part variation into account in the assembly simulation, the variation of the individual part geometry realistic, simulated deformations.

2. Assembly simulation with *ANSYS*

   The second step is the assembly simulation with *ANSYS*. With the chosen simulation model, it is possible to account for the sheet thickness distribution, a provided stress state and the (deviating) geometry of each individual part. In addition, it is possible to map the current configuration of the fixture. This includes the kinematics of the fixture units, clamping and joining sequence as well as the position of the clamps in the fixture. The assembly simulation process can be divided into several steps: First, the individual parts are inserted into the fixture, then the clamps are closed, the individual parts are joined by connecting nodes, the clamps are released and finally the joined assembly

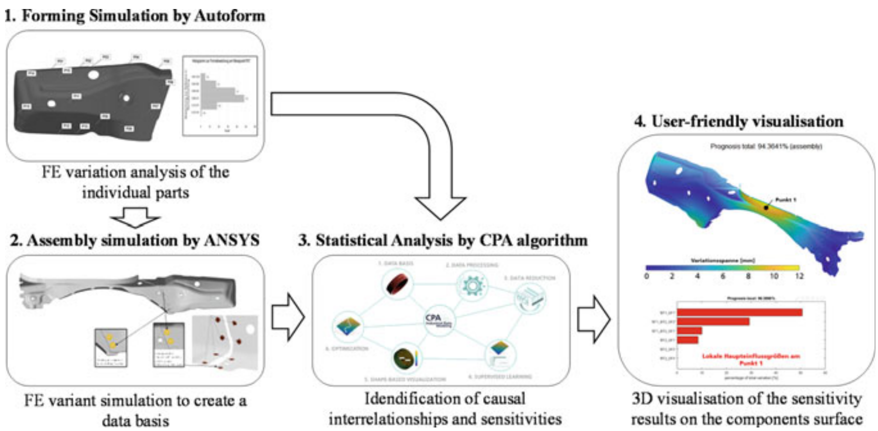


Fig. 2 Developed concept to identify process relevant parameter

(positioned according to RPS) is measured to determine the deviation between measurement and reference geometry (CAD).

The primary objective of the study is to identify changes in the dimensional quality of the assembly as a consequence of a defined adjusting of the clamps of the fixture. In order to systematically generate input data for the CPA algorithm, a design of experiments (DOE) plan is created with various settings of the clamps of the fixture. In the context of the investigation, the simulation model has been extended so that various settings of the clamps of the fixture can be implemented and corresponding simulations are calculated automatically.

3. Statistical analysis by CPA algorithm

   Based on the *ANSYS* simulation data, CPA is used to identify how the clamps of the fixture varied in step 2 and influence the dimensional accuracy of the assembly. For this purpose, a surrogate model is built, which approximates the relationship between clamps settings and part geometry.

4. User-friendly visualization

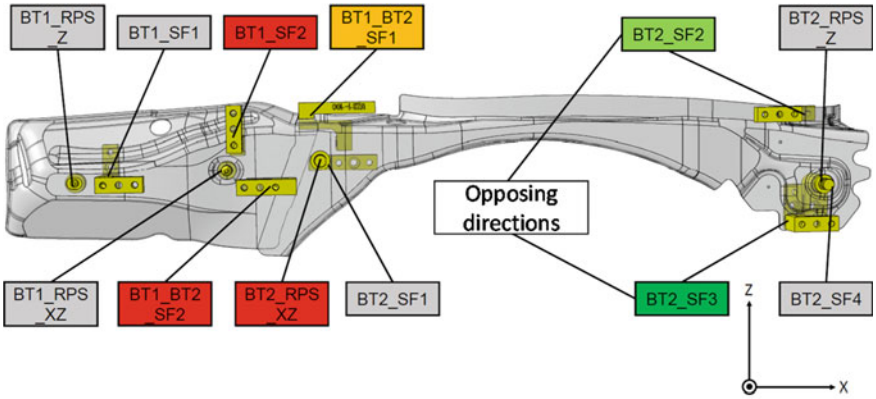
   With the CPA algorithm, the calculated sensitivities of the clamps can be visualized node-based on the FE mesh surface in the last step.

Sensitivity Analysis of a Wheelhouse Sub-Assembly

In the first case study, the presented concept is applied to a two-piece sub-assembly of a wheelhouse. The aim is to identify the influence of six clamps of the fixture on the dimensional quality of the sub-assembly. Figure 3 shows the varied input parameters within the simulation model.

Based on the input parameters, ten samples are generated using a random-based sampling strategy (Latin hypercube), and the final dimensional accuracy is calculated for each test variant using the *ANSYS* simulation engine. The resulting FE meshes are standardized as an input for the CPA algorithm, where they are linked to the input parameters by statistical models. For analyzing the sensitivity effects of the clamp parameters, a *MATLAB*-based graphical user interface (GUI) was designed, with which the user is able to apply the CPA algorithm independently and menu-driven. The mesh-based results of the CPA method for identifying cause–effect relationships can be seen in Fig. 4.

The results show that the prognosis quality of the CPA model is very high. A total prognosis of approx. 94% (coefficient of determination) can be achieved. The upper bar chart in Fig. 4 on the left shows that the clamp parameter "BT1_SF1" has the greatest influence on the dimensional accuracy with almost 50%, followed by the clamp parameter "BT1_BT2_SF2" with 27%. Likewise, the local sensitivity on each FE-node of the entire *ANSYS* mesh can be determined by the CPA model. The lower bar chart in Fig. 4 shows the impact of the different clamp parameters on a single point 1 (position is indicated on the right-hand side of Fig. 4). The point lies in an area



Sample	Variation of clamp parameters [mm]					
	BT1_SF1	BT1_BT2_SF2	BT1_BT2_SF1	BT2_SF1	BT2_SF2	BT2_SF4
0	0	0	0,0	0	0	0
1	0,7	1,6	0,3	5	0,6	-1,9
2	-5	-5	0,8	0	-0,7	1,1
3	2,7	4,7	0,1	-5	-2,5	-1,8
4	5	3,3	0,6	1,4	-1,7	2,2
5	-0,7	3,5	0,4	3,9	-1,1	-0,3
6	-2	1,7	0,9	-3,8	-0,5	2,5
7	-3,1	3,1	0,7	1,1	2,2	1,9
8	-2,1	5	0,1	-2,7	2,5	-2,5
9	-3,2	-5	0,2	0,7	1,4	1,6
10	2,3	3,8	0,5	1,6	2,4	-0,8

Fig. 3 Varied input parameters within the simulation model

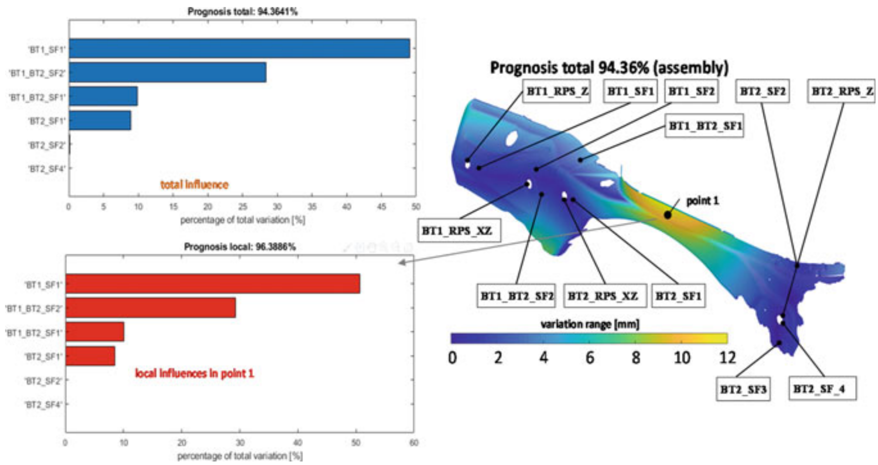


Fig. 4 CPA results of the wheelhouse sub-assembly

with a very high variation range of about 8 mm (Fig. 4—right). A local prognosis value of approx. 96% can be obtained here. Due to the high prediction quality of the model, it can be stated that the CPA model works well for this multi-part body assemblies.

Sensitivity Analysis of a Structural Side Panel

With the developed procedure, it is also possible to simulate the manufacturing process of more complex assemblies; such as the structural side panel shown in Fig. 5. The assembly, which is produced in four (sub)-assembly stages, consists of nine individual parts. One simulation result with a modification of the clamping settings in the last assembly stage is shown as an example. The so-called *shim task* causes the *b-pillar* to rotate transverse to the driving direction (around the y-axis). Figure 5 visualizes the clamp and pin positions in fixture (P_n). The rotation of the *b-pillar* by approx. 5 degrees is achieved by adjusting the P4, P10, P13, P24, P44, and P45. In addition, the *b-pillar* is displaced by 0.1 mm in opposite driving direction. Figure 5 includes the quantitative adjustments of the clamps and pins (P_n).

Figure 6 shows the simulation result with rotated *b-pillar*. The maximum deviation to the reference at the assembly amounts to 3.7 mm in the transition area to the *roof rail* (*M3* in Fig. 6). This simulation result—as one among many (n > 10)—is used

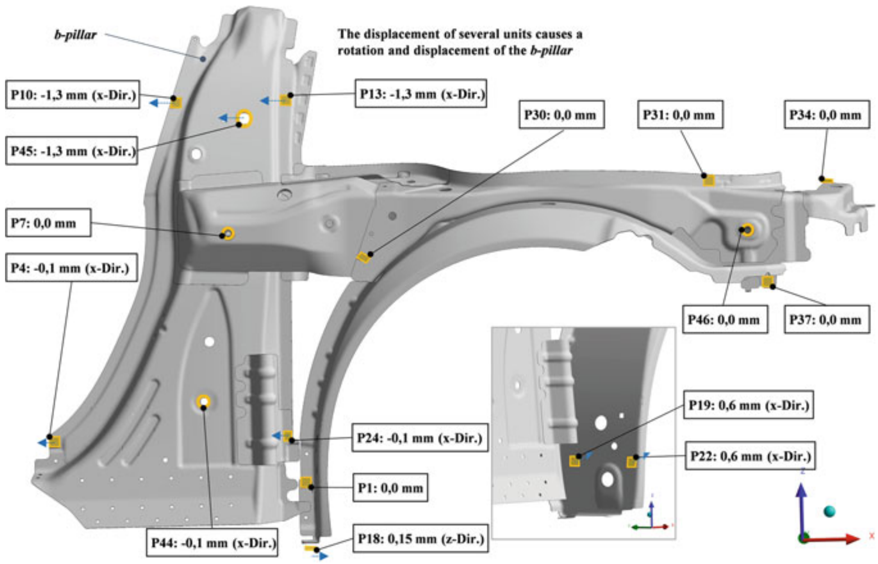


Fig. 5 Clamp and pin positions in structural side panel fixture (P_n) and the belonging adjustment value

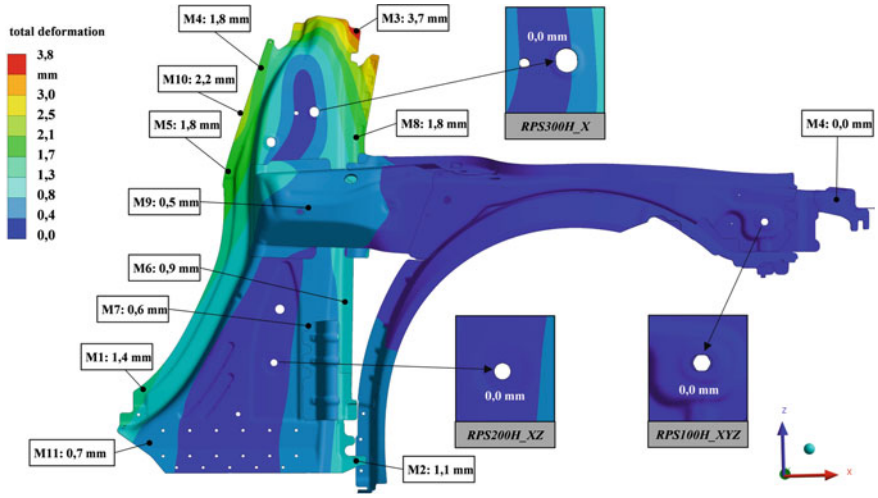


Fig. 6 Simulation result; *total deformation* as a measure of deviation from the reference geometry

by the CPA algorithm to create a surrogate model for predicting the influence of a *shim task* on dimensional accuracy of the assembly (Fig. 7).

Again, a high prognoses quality of approx. 91% is achieved. The clamp group 1, located at the bottom of the *b-pillar*, has major influence on the dimensional accuracy. Further validation with practical test series is pending.

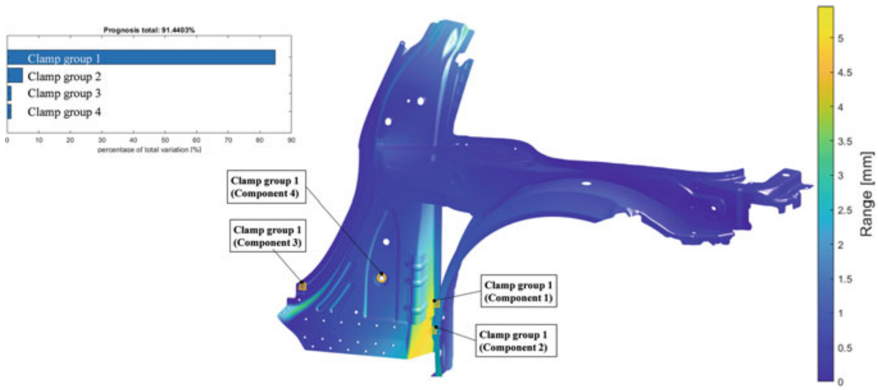


Fig. 7 CPA results of the structural side panel assembly

Conclusion

The construction of dimensionally accurate car body assemblies is a huge challenge in automotive industry. Complex multi-step joining procedures, involving diverse process uncertainties, do not admit simple cause–effect relationships between clamp parameter adjustments and resulting geometrical deviations in the joined assembly. The present paper suggests a new approach based on simulation and statistics, which is able to approximate these interactions to a large extend.

It is possible to map the manufacturing process, involving the stamping process, the assembly and the measurement, completely virtually (*AutoForm, ANSYS*). The resulting assembly geometries for varying process input parameters (stamping parameters as well as clamp settings) are given as input to a prediction model based on Coupled Process Analysis (CPA). Here, also measurement data can be provided. Based on the input data, CPA is used to identify how the clamps of the fixture varied in the step before influence the dimensional accuracy of the assembly. For this purpose, a surrogate model is built, which approximates the relationship between clamps settings and part geometry. The results show that the effect of the clamp settings can be predicted with a high accuracy via statistical models even for complex assemblies.

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