Variance based sensitivity analysis of deep drawing processes based on neural networks using Sobol indices

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Abstract. Today’s deep drawing of car body parts is operated increasingly closer to the process limits, making it more challenging to ensure a high robustness of the process. Disturbances like varying material properties or changing tribological conditions may negatively affect the process, leading to deteriorated product properties and a loss of productivity. In the past, several approaches using different combinations of sensors and actuators have been investigated to fulfill the need of a more robust process. Hence, a thorough process analysis comes to be beneficial to evaluate the expediency of a control system and to make a reasonable preselection of sensors in order to avoid unnecessary costs. This paper presents a method using variant simulations to evaluate the expediency of a control system, including the necessary sensors. The influence of disturbances in the process is evaluated by a numerical sensitivity analysis under consideration of interaction effects. These higher order effects are calculated by Monte Carlo integration. Potential measurands are determined by the maximum achievable observability of not directly measurable quality criteria of a part. For this purpose, different modelling approaches of the observability are considered and compared with regard to their goodness-of-fit.

1. Introduction and state of the art

Approximately 30% of the total car’s weight is due to the body-in-white making it to the heaviest part of modern conventional vehicles. Thus, the application of principles and strategies of modern lightweight design is of crucial importance to the weight reduction in the vehicle production in order to assure a long-term competitiveness and a sustainable and financially affordable mobility [1]. Apart from the use of innovative multi-material concepts and multiphase steels, the thickness of the metal sheets is decreasing steadily in adherence to complex part geometries and high production rates to achieve these goals [2]. The assurance of a stable and robust process is becoming more and more challenging since deep drawing of car body parts is operated increasingly closer to the process limits [3]. Minimal process fluctuations like varying material properties or changing tribological conditions as well as a lack of knowledge of the process may already cause part failure and thereby diminish productivity [4]. In the past, several approaches using different combinations of sensors and actuators have been investigated aiming to increase the robustness of the process based on a closed or open loop control system. The concept of the systems mainly distinguishes between a part-to-part control [5] and the control during the stroke [6], depending on the available actuators and sensors. Most control systems rely on the inline data acquisition of the flange draw-in of the deep drawn part, since the material flow is one of the few
measurands that allows to draw conclusions regarding the part quality during the forming process [6]. Although several reliable data acquisition methods are available and control systems have been investigated extensively in a laboratory [6][7] and production scale [5][8], a general preceding process analysis regarding the expedience of a control system in series production is often simplified or neglected. In [9] a methodological approach to verify the feasibility of a process control in deep drawing is presented. However, the approach aims at verifying the application of a metamodel based control system that uses, in particular, draw-in measurements as a control variable. Furthermore, a full sensitivity analysis considering first order and higher order effects is not taken into account.

This paper presents a general method for a process analysis using variant simulations to make a preselection of measurands and sensors and to evaluate the expedience of a control system or alternative concepts like an operator assistance system. Different modelling approaches considering various levels of complexity based on variant simulations are discussed regarding their goodness-of-fit and suitability for a further process analysis. Five typical core panels of car manufacturers are compared and analysed in terms of their sensitivity to changes in disturbance variables as well as their virtual process robustness and observability to enable a preselection of sensors and to evaluate the expedience of a control or operator assistance system.

2. Methodology of the process analysis
The schematic for the process analysis is shown in Figure 1. Once a component to be analysed has been selected, a numerical simulation of the corresponding process is set up. The design of experiments (DoE) is generated by a Latin hypercube sampling under the consideration of the variation ranges and the probability distributions per parameter as well as the correlations between the parameters. Based on the results gained from the variant simulations, several regression models are trained depending on the achievable goodness-of-fit per model as well as the input and output parameters needed for the process analysis. The most influential input parameters on a selected quality criterion (output) are investigated based on first order effects and total effects using Monte Carlo integration. The robustness of the process is evaluated by the defects per million opportunities (DPMO) to determine the effectiveness of the process and to allow a comparison between different processes.

![Figure 1. Schematic of the process analysis.](image-url)

A recommendation and preselection for sensors is made based on the maximum achievable observability considering different combinations of measurands. For the analysis of the controllability and the derivation of a compensation strategy, it is recommended to run more advanced numerical
simulations considering elastic tool behaviour and advanced friction models. However, the analysis of the controllability and the derivation of a compensation strategy are not part of this work. Detailed information on the compensation of negative frictional effects using friction models in a thermomechanical simulation can be found in [10].

3. Variant simulations of core panels from automobile manufacturers

The general business trend among car manufacturers to move from an in-house manufacturing operation to an outsourced one also applies to the production of car body parts. Today, most car manufacturers mainly focus on outer body parts and structural parts are increasingly produced by suppliers. For this reason, the five panels from the current production chosen for the investigation in this work mainly represent outer body parts made of mild steels. An overview, including the key features per part is shown in Table 1. The parts are sorted by their drawing depth, providing depths between 80 mm for a roof and up to 230 mm for a tailgate outer. All panels are produced from a hot dipped galvanized (HDG) mild steel, except for the roof with an electro galvanized (EG) coating.

Table 1. Application examples with increasing drawing depths.

| Model  | Material | Coating | Width x length | Drawing depth |
|--------|----------|---------|----------------|--------------|
| Roof   | Insignia B | CR4 | 1965 x 1320 mm | 80 mm |
| Hood   | Crossland X | CR180B2 | 1820 x 1085 mm | 110 mm |
| Tailgate inner | Astra K | CR4 | 1470 x 1175 mm | 120 mm |
| Tailgate well | Insignia B | CR180B2 | 1750 x 1045 mm | 225 mm |
| Tailgate outer | Astra K | CR4 | 1610 x 1170 mm | 230 mm |

Variation simulations of a numerical baseline simulation are carried out in order to assess the behaviour of the parts when any material or process parameter changes. The design of experiments is generated by a Latin hypercube sampling using 151 simulations for each part based on the commercial finite element software Pam-Stamp from ESI. Uniaxial tensile tests and hydraulic bulge tests have been used as a data basis for the material modelling. The simulations use a yield curve approximated as proposed by Swift/Krupkowsky [11] and a Hill90 [12] yield locus, except for the hood, which is based on a Hill48 yield locus [13].

Table 2. Parameters and its ranges for the variant simulations.

| Parameter      | Roof | Hood | Tailgate inner | Spare wheel well | Tailgate outer |
|----------------|------|------|----------------|------------------|---------------|
| Friction coeff. | 0.069-0.095 | 0.069-0.095 | 0.069-0.095 | 0.069-0.095 | 0.069-0.095 |
| BH force       | 1500-1700 kN | 950-1050 kN | 1500-1700 kN | 1200-1800 kN | 1200-1400 kN |
| Blank thick.   | 0.69-0.71 mm | 0.58-0.62 mm | 0.64-0.66 mm | 0.62-0.67 mm | 0.64-0.66 mm |
| Yield str.     | 141-178 MPa | 184-230 MPa | 145-179 kN | 197-241 MPa | 145-179 kN |
| Tensile str.   | 282-314 MPa | 300-337 MPa | 282-312 MPa | 289-353 MPa | 282-312 MPa |
| r-value (0°)   | 1.51-2.19 | 1.34-2.21 | 1.59-2.20 | 1.82-2.72 | 1.59-2.20 |
| r-value (45°)  | 1.23-1.79 | 0.96-1.59 | 1.30-1.80 | 1.26-1.88 | 1.30-1.80 |
| r-value (90°)  | 1.90-2.75 | 1.47-2.45 | 2.00-2.77 | 1.99-2.99 | 2.00-2.77 |
| n-value        | 0.21-0.24 | 0.18-0.22 | 0.21-0.24 | 0.18-0.22 | 0.21-0.24 |
| x-pos. blank   | +/- 5 mm | +/- 5 mm | +/- 5 mm | +/- 2.5 mm | +/- 5 mm |
| y-pos. blank   | +/- 5 mm | +/- 5 mm | +/- 5 mm | +/- 2.5 mm | +/- 5 mm |
The forming limit curves (FLC) of the baseline simulations have been determined by Nakajima tests [14], whereas the Keeler-Godwin approach [15][16] has been used for the variants. The variation range of each parameter, as shown in Table 2, has been derived from measurements and internal material databases of uniaxial tensile tests. The thickness of the blank sheet is deduced from inline measurements in the coil line, whereas the constant friction coefficients have been estimated based on strip drawing tests considering different tool temperatures (20 – 60 °C), contact pressures (2 – 10 MPa) and sliding velocities (10 – 300 mm/s).

4. Setup of regression models

Based on the results from the numerical variant simulations, it is possible to estimate a relationship between a dependent variable Y such as a selected quality criterion and an independent variable such as the varied parameters Xᵢ. In general, the regression models are a function of the independent variable.

\[ Y = f(X) = f(X₁, ... , Xₖ) \] (1)

Such regression techniques using simulation data are often referred to as metamodels and can be calculated by a variety of approximation or interpolation approaches. In forming technology, either the approximating response surface methodology such as multiple linear regression (MLR) or multiple quadratic regression (MQR) models (including or excluding interaction terms) and interpolating approaches such as radial basis functions (RBF) have been established [17][18][19]. In this work, these models will be used to calculate the quality criterion rupture risk derived from the forming limit diagram (FLD). The results are compared with the two commonly used machine learning approaches support vector machines (SVM) and multilayer artificial neural networks (ANN) regarding its goodness-of-fit, as shown in Table 3. The quality and performance of the models is evaluated by the coefficient of determination \( R^2 \) based on a 7-fold cross-validation, so approximately 15 % of the data set of 151 simulations per part is used as independent test data. With regard to the SVM models, either a linear or polynomial kernel has been used. Furthermore, the neural networks are trained by the Levenberg-Marquardt algorithm [20] under consideration of 70 % training data and 15 % validation data.

| Table 3. Maximum achieved coefficients of determination for the modelling of the rupture risk. |
| --- |
| Model type | R² | Roof | Hood | Tailgate inner | Spare wheel | Tailgate outer |
| --- | --- | --- | --- | --- | --- | --- |
| 1) MLR | | | | | | |
| R² Train. | 81.25% | 17.88% | 21.94% | 72.27% | 53.78% |
| R² Test | 77.01% | 12.02% | 22.98% | 72.07% | 45.95% |
| R² All | 80.99% | 17.17% | 20.82% | 71.73% | 53.36% |
| 2) MQR | | | | | | |
| R² Train. | 83.81% | 32.22% | 61.84% | 79.40% | 66.28% |
| R² Test | 71.19% | 19.76% | 42.56% | 65.03% | 53.38% |
| R² All | 82.78% | 29.53% | 57.03% | 77.71% | 63.75% |
| 3) RBF | | | | | | |
| R² Train. | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% |
| R² Test | 4.12% | 3.84% | 8.70% | 1.56% | 2.99% |
| R² All | 39.33% | 85.47% | 85.69% | 81.15% | 85.74% |
| 4) SVM | | | | | | |
| R² Train. | 80.59% | 99.99% | 100.00% | 71.20% | 99.97% |
| R² Test | 77.91% | 11.38% | 12.21% | 79.05% | 47.43% |
| R² All | 80.28% | 52.14% | 78.60% | 71.28% | 92.33% |
| 5) ANN | | | | | | |
| R² Train. | 90.86% | 97.74% | 99.51% | 99.68% | 93.43% |
| R² Val. | 87.96% | 86.55% | 98.61% | 91.15% | 87.80% |
| R² Test | 92.82% | 97.36% | 96.60% | 94.59% | 92.44% |
| R² All | 90.48% | 94.47% | 98.49% | 96.94% | 92.43% |
| Neurons | [43, 58, 22] | [10, 10, 10] | [11, 18, 11] | [10, 16, 18, 14] | [11, 13] |
The model types 1) – 4) are deterministic in terms of the achieved global optimum in contrast to artificial neural networks. To deal with this issue, boundary conditions regarding the maximum number of neurons and hidden layers have been set up to define a final abortion criterion of the calculation. Each hidden layer consists of 10 to 60 neurons and the depth of the neural network is limited to four hidden layers. The calculation ends, when a depth of four hidden layers and 60 neurons per layer is reached, unless the minimum R² of 86.5 % is reached for the training, validation and test phase. Although the calculation of an ANN model appears to be the most expensive one, the results indicate to be the most reliable and robust regarding the estimation of the rupture risk of the parts considered here. Comparatively low complex models like the MLR or MQR including interaction terms provide robust results, since there is mostly no high deviation between the R² of the training and test data. However, these models can only provide an acceptable goodness-of-fit for the roof and spare wheel well. The same applies for the SVM models, even though they have a strong tendency to data-overfitting, especially for polynomial kernels as the R² of the test data shows. RBF models are the least suitable for the present cases due to their low goodness-of-fit with respect to the test data.

5. Process analysis
The implementation of a control system or alternative concepts like an operator assistance system is not beneficial and may cause unnecessary costs if the process is sufficiently robust. In contrast, the selection of suitable sensor technologies is becoming increasingly important when such solution approaches are being considered. However, a deeper process understanding is neglected, if the evaluation of the experience of such solution approaches is focusing on robustness performance indicators, observability and controllability only. Therefore, a variance based sensitivity analysis using Sobol indices is also performed in this work to identify root causes for main failure modes or quality criteria. As before, the quality criterion rupture risk is selected for the process analysis of the five application examples.

5.1. Variance based sensitivity analysis
Global sensitivity analysis methods are becoming increasingly popular due to their ability to deal with complex models. These methods are generally variance based and do not rely on linearity, monotonicity or continuity and can be applied to a wide range of problems [21]. The concept is based on the idea of using the variance as an indicator of the importance of an input parameter in terms of fractional contribution to the output variance \( V(Y) \). The analysis of the variance decomposition is often referred to as the Sobol method following [22][23] and allows the measurement of main effects of an input parameter by varying \( X_i \) alone (first order sensitivity index \( S_i \)) as well as the total effect, which additionally includes all variance caused by its interactions (total order sensitivity index \( S_{Ti} \)). The computation of the Sobol indices is based on the decomposition of the function \( f(X) \) into summands of increasing dimensionality and requires the solution of multidimensional integrals [22]. Thus, the indices are estimated by the Monte Carlo method in the vast majority of cases. According to the investigation of Saltelli et al. [24], the Jansen estimators [25] are recommended as the most efficient in terms of computational costs. The estimations of \( S_i \) and \( S_{Ti} \) according to Jansen used in this work are defined as:

\[
S_i \approx \hat{S}_i = \frac{V(Y) - \sum_{j=1}^{n} (f(B_j) - f(A^{(i)}))}{V(Y)} \tag{2}
\]

\[
S_{Ti} \approx \hat{S}_{Ti} = \frac{\sum_{j=1}^{n} (f(B_j) - f(A^{(i)}))}{V(Y)} \tag{3}
\]

The index \( i \) runs from one to \( k \), the number of factors, while the index \( j \) runs from one to \( n \), the number of simulations. The matrices \( A \) and \( B \) are two independent sampling matrices based on the Latin hypercube sampling, with \( a_{ij} \) and \( b_{ij} \) as generic elements. The matrix \( A^{(i)} \) contains all columns from \( A \) except the \( i \)-th column, which is from \( B \).
The design of $A_{ij}^{(l)}$ is based on the so-called radial design, presented in [26] and recommended in [24]. Based on the results from Table 3, the sensitivity analyses have been carried out using the ANN models of the rupture risk (Table 4). The error and share of influences that cannot be explained by the model is included as ‘Unknown’. Moreover, the Sobol indices are standardized based on the R²-All. The results indicate the processes in this study to be mainly driven by the material properties and the friction in terms of the rupture risk. The influence of the blank holder force, the blank thickness and the position of the blank are not significant in most cases, except for the roof, which is highly influenced by the blank holder force. In particular, the processes of the tailgate inner and the tailgate outer show that the consideration of interaction effects can lead to a higher influence of material properties. One possible explanation might be that unfavourable combinations between the tensile and yield strength deteriorate the flow behaviour of the material (high yield strength and low tensile strength). The same might apply for combinations of low $r$-values. A comparison between the processes also implies an increasing influence of the friction with increasing drawing depths, since the friction influence is highest for the tailgate outer and lowest for the hood and roof. In contrast, material properties appear to be increasingly influential for lower drawing depths.

### 5.2. Evaluation of the process robustness based on variant simulations

Although a sensitivity analysis enables the identification of root causes of part failures and leads to a deeper process understanding, it does not allow statements with regard to the process robustness. Probably the easiest and most reliable way to identify challenging processes is to evaluate shift reports of processes from the series production. However, since a sound data basis might not be available at an early stage after the start of production, simulation results can be a good alternative. The virtual evaluation of the process robustness and performance can be done by calculating the defects per million opportunities (DPMO), which has the advantage of considering multiple defects of the same type and does not rely on an upper and lower specification limit such as the Cpk-value. Thus, the DMPO is a suitable criterion to assess robustness based on the rupture risk, which only respects an upper limit. The simulation results are classified into three different categories in terms of rupture risk (Figure 2a). The offset of 10 % to the FLC (safety barrier) is derived from internal guidelines. Simulations containing nodes above the FLC are considered as failed parts (NOK), simulations with all nodes below the safety barrier as good parts (OK) and the remaining results are classified as critical. Table 5 includes all DPMO values per part and class, while the total DMPO is summarized in Figure 2b. Processes with expected scrap rates above 5 % can be considered as critical. In this study, this applies to the spare wheel well and the tailgate outer, which must therefore be taken into account when considering the implementation of a control system.

### Table 4. Parameters affecting the rupture risk.

| Parameter          | Roof | Hood | Tailgate inner | Spare wheel well | Tailgate outer |
|--------------------|------|------|----------------|------------------|---------------|
| Friction coeff.    | 20.6%| 19.3%| 8.1%           | 48.9%            | 57.3%         |
| BH force           | 25.2%| 28.0%| 5.1%           | 4.6%             | 8.1%          |
| Blank thick.       | 1.5% | 2.3% | 5.3%           | 4.3%             | 1.0%          |
| Material prop.     | 38.8%| 39.6%| 67.7%          | 64.3%            | 55.9%         |
| Position blank     | 4.4% | 1.2% | 8.2%           | 7.6%             | 6.0%          |
| Unknown            | 9.5% | 9.5% | 5.5%           | 5.5%             | 3.1%          |

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Table 4. Parameters affecting the rupture risk.
Figure 2. Classification of the simulation results based on the FLD (a) and total DPMO per part (b).

However, the hood, the roof and the tailgate inner are expected to ensure a sufficient process robustness in terms of rupture. The results are in line with the experience from series production. Necking and ruptures are one of the main failure criteria of the tailgate outer and the spare wheel well, while the roof and the hood in particular usually suffer from surface defects caused by particles of zinc coating.

Table 5. Defects per million opportunities.

| Rupture risk | Roof | Hood | Tailgate inner | Spare wheel well | Tailgate outer |
|--------------|------|------|----------------|------------------|---------------|
|              | %    | %    | %              | %                | %             |
| Critical     | 13,245 | 1.32% | 0 | 2,208 | 0.22% | 23,061 | 2.31% | 16,556 | 1.66% |
| NOK          | 0 | 0.00% | 18,212 | 1.82% | 15,453 | 1.55% | 32,495 | 3.25% | 57,947 | 5.79% |
| TOTAL        | 13,245 | 1.32% | 18,212 | 1.82% | 17,661 | 1.77% | 55,556 | 5.56% | 74,503 | 7.45% |

5.3. Preselection of sensors based on observability

Observability of the deep drawing process is considered in the context of this work as the ability to derive not directly measurable quality criteria of a part on the basis of available measuring systems and serves the preselection of relevant measurands. It is a generalisation of the definitions from [9] and [27], which solely refer to the flange draw-in as measurement option and is not to be confused with observability in control theory. Different combinations of measurable parameters serve as input to calculate the quality criteria rupture risk based on the MQR including interaction terms. Between 8 and 12 draw-in positions are chosen randomly per part. The observability per combination is quantified by the achievable R² after cross-validation (Table 6). In a first step, a stepwise regression based on the backward elimination approach is carried out to determine the optimal combination of measurands per process. For this purpose, a combination set considering all parameters is used as the model input (combination set no. MQR6). Only parameters with an added value to the goodness-of-fit will be left in that model, i.e. not all draw-in positions or material parameters are necessarily included. The results of these ideal combinations per part are highlighted by underline in Table 6. The measurement of the draw-in and the material properties (no. MQR4) appear to be the most promising solution for all processes, except for the hood. Therefore, draw-in sensors combined with an eddy current system to measure material properties are probably the most suitable solution. However, the measurement of the sole draw-in already provides a sufficient observability in all cases, except for the hood and can be extended by measuring the blank position, e.g. by using laser triangulation sensors. This is in agreement with the results of the sensitivity analysis regarding the influence of friction and material properties, taking into account that the draw-in is a suitable indicator to reflect changes of the frictional behaviour as well as
changes of the blank holder force [28]. Thus, the blank holder force can be represented by the draw-in and its additional measurement does not provide a significant advantage. Considering the blank holder force or blank thickness may even affect the observability adversely, as shown by combination no. MQR6. Furthermore, a sole measurement of material properties is not recommended for any of the processes due to the low R² of the MQR. Even if all processes appear to be observable in terms of rupture risk, the application of a more complex model like ANN allows the reduction of the number of necessary measurands without significant loss in the performance (no. ANN1) compared to the ideal set, or at least an increase of the observability.

Table 6. Modelling of the rupture risk under consideration of different measurand combinations.

| No.   | Combination of parameter | Roof inner | Hood | Tailgate inner | Spare wheel well | Tailgate outer |
|-------|--------------------------|-----------|------|----------------|------------------|---------------|
| MQR1  | Draw-in                  | 76.54%    | 34.45% | 90.01%         | 84.08%           | 86.97%        |
| MQR2  | Material prop.           | 59.72%    | 27.57% | 32.19%         | 18.35%           | 32.57%        |
| MQR3  | Draw-in Position blank   | 85.03%    | 69.22% | 92.60%         | 87.42%           | 94.75%        |
| MQR4  | Draw-in Material prop.   | **95.60%**| 78.50% | **99.50%**     | **98.19%**       | **99.93%**    |
| MQR5  | Draw-in Blank thick.     | 88.48%    | 72.32% | 94.19%         | 87.58%           | 90.07%        |
| MQR6  | Draw-in Blank thick.     | 91.47%    | **96.74%**| 98.51%         | 95.24%           | 96.63%        |
| ANN1  | Draw-in                  | 84.58%    | 82.14% | 98.08%         | 90.49%           | 95.19%        |
| ANN2  | Material prop.           | 75.44%    | 79.73% | 71.58%         | 51.65%           | 62.62%        |

6. Conclusions and outlook

The approach of a process analysis using variant simulations proposed in this work enables the identification of necessary measurands and the evaluation of the expedience of a control system or alternative concepts such as an operator assistance system. Five different deep drawing processes of car body parts are analysed in terms of their expedience for a control system using the DPMO as a performance index of its process robustness. The two processes with the highest drawing depths are worth considering regarding the implementation of a control system. However, all processes are observable and the observability analysis allows to deduce a preselection of sensors. In general, the highest observability is reached under the consideration of a draw-in measurement. The process analysis is complemented by a deeper process understanding due to a variance based sensitivity analysis using Sobol indices. Varying material properties and changing friction conditions can be considered as the main driver influencing the rupture risk of car body parts made of mild steels. An increasing influence of friction with increasing drawing depths could be observed, while material properties tend to have a higher significance for lower drawing depths. The next logical step is the analysis of the controllability and the derivation of a compensation strategy on the one hand. On the other hand, the implementation of a suitable measurement system has to be concretised in terms of functional, structural and economic aspects, which highly depend on the specific circumstances in the manufacturing press shop.

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