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Metamodel-based methods to verify the feasibility of a process control in deep drawing

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Metamodel-based methods to verify the feasibility of a process control in deep drawing

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Abstract. In production of deep drawn sheet metal parts it is often challenging to achieve a robust process. Especially in the production of kitchen sinks made out of stainless steel, the fluctuation of the process and material properties often lead to robustness problems. Therefore, numerical simulations are used to detect critical regions. By means of a series of finite element simulations with variable noise and design parameters, metamodels are computed for each quality criterion. Based on the metamodels, the influences of changing noise variables on the individual quality features are identified. To keep a constant product quality, the process settings (design parameters) should be adjusted. By means of new metamodel-based methods, the controllability of quality features is verified for user-defined production scenarios and visualised for each design and noise parameter. Thus it is possible to identify which design parameters are indispensable to control the desired quality feature and if it is controllable depending on the actual values of the noise variables. Furthermore the controllability of the entire part is analysed by using draw-in measurements for the feedback loop. Thereby it is possible to simulate, based on the metamodels, the effects of a series production, such as the heating of the tools during the first dozen of parts. Hence, the feasibility of a process control can be verified before realisation in order to optimize the concept of process control or even the process design.

Keywords: Deep drawing simulation, metamodel-based methods, process control, optimisation

1. Introduction

The presented part is a kitchen sink made out of austenitic stainless steel (1.4301) produced by Franke. The material is characterised with tensile experiments at a range of temperatures, Bulge and Nakajima tests. Because of strain-induced martensite the hardening behaviour is strongly temperature dependent. Therefore the Hänsel model is fitted to approximate the hardening behaviour, the BBC yield locus model is fitted and the measured FLC from Nakajima tests is used in simulation (complete material card under [8] from material B).

The effects of increasing temperature during serial production or changing material batch affect the production and thus the kitchen sink quality. In order to keep a constant part quality, variant simulations are computed. The influences of disturbances (e.g. material properties, temperature, friction) and the control variables (e.g. press forces) on the quality features are then used in metamodels, which form the
basis for subsequent process control [4] [5]. The metamodels are used to design and verify the feasibility of process control based on a methodological approach. Thus, a simulative verification of the effectiveness and evidence of process control is performed before acquiring additional hardware.

In the subsequent sections the two terms *Observability* and *Controllability* have not the same meaning as in control technology. In this manuscript, they describe the literal meaning to observe a characteristic on the part or rather to change a feature by adjusting some specific parameters.

2. Methodological approach

Nowadays, nearly every deep drawing geometry is designed and simulated in methodology planning with various software packages before realisation of the hardware. Many simulation tools also offer the possibility to analyse the process robustness or to optimise design parameters to increase robustness. The growing importance of Smart Factories, in particular process control, requires methods to design the concept and check the feasibility of such a process control. None of the commercial simulation software packages provide a solution. Therefore, a methodological approach is presented based on variant simulations.

- Compute variant simulations (AutoForm Sigma, LS-Opt, PAM-Stamp, MSC Marc, etc.)
- Define quality criteria (Splits, wrinkling, springback, …)
- Define corresponding draw-in sensors
- Calculate metamodels
- Visualise process windows
- Assess process robustness
- Evaluate observability
- Evaluate controllability of individual sensor and of all sensors

The process control is realised based on sensors to monitor the material flow [1]. In order to avoid tool-specific sensors the draw-in is measured after the first deep drawing operation with a camera [4]. In the following sections the individual modules are explained in detail.

3. Variant simulations, quality criteria and draw-in sensors

The baseline simulation is first calibrated with a digitised part from production after the first operation. Therefore, the simulation parameters are set as the real process conditions, such as binder force distribution, force reduction during drawing, blank position, material properties (measured material model) and blank thickness. The unknown parameters, such as the friction coefficient, are optimised in order to reduce the draw-in difference between the real part and the simulation [6]. Around the calibrated simulation the disturbance and actuating variables are varied in a specific range based on process data and measurements (see Table 1).

**Table 1: Variation parameters and range (grey: not varied or dependent of other parameter)**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Binder force A $F_A^{(A)}$</td>
<td>1050 kN</td>
<td>1850 kN</td>
</tr>
<tr>
<td>Binder force B $F_B^{(B)}$</td>
<td>1000 kN</td>
<td>1800 kN</td>
</tr>
<tr>
<td>Die cushions 2 and 4 (each)</td>
<td>150 kN</td>
<td>150 kN</td>
</tr>
<tr>
<td>Die cushion 3</td>
<td>60 kN</td>
<td>240 kN</td>
</tr>
<tr>
<td>Die cushion 1, (inverse of 3)</td>
<td>240 kN</td>
<td>60 kN</td>
</tr>
<tr>
<td>Blank position $x_{\text{blank}}$</td>
<td>-5 mm</td>
<td>10 mm</td>
</tr>
<tr>
<td>Friction $\mu$</td>
<td>0.05</td>
<td>0.086</td>
</tr>
<tr>
<td>Tool temperature $T$</td>
<td>25°C</td>
<td>40°C</td>
</tr>
<tr>
<td>R-values $r_{90}, r_{45}, r_{90}$</td>
<td>-10 %</td>
<td>+10 %</td>
</tr>
<tr>
<td>Blank thickness $t_{\text{blank}}$</td>
<td>0.775 mm</td>
<td>0.825 mm</td>
</tr>
</tbody>
</table>

*Figure 1: Position of die cushions under binder*
The total binder force is set to much higher forces during the first section of the stroke until 95 mm before bottom dead centre (BDC) (binder force A). Then the forces are reduced linearly until 75 mm and stay constant until the end of the stroke (binder force B). In the design of experiments the two global binder forces are varied independently ($F_G^A$ and $F_G^B$).

Based on the simulations computed in AutoForm Sigma, the determined quality criteria are defined. A similar geometry has been analysed in [6], whereby for the part pictured in Figure 2 only splits in the bottom and wrinkles in the side wall of the sink are critical. For each quality criterion one limit value is defined to generate process boundaries. For the thinning in the sink bottom the limit is set to 0.25 according to the measurement of the digitised part.

After this step the draw-in measurement positions are defined based on the correlation values. Figure 2 (right) shows the correlations in colour between the split criterion in the sink bottom and the draw-in values. For the presented part, six draw-in measurements are used to realise the process control.

### 4. Process windows and process robustness

For each quality criterion and each sensor value one metamodel is calculated. Based on the previously defined limits of the quality criteria, process windows are visualised. As presented in [7], the influence of up to four varied parameters on the individual process boundaries can be shown. Furthermore the influence of scattering material properties on the process window size can be illustrated, as shown in [6]. Thus, the impact on the remaining process window size is shown at a glance.

Processes, which are designed close to the limits of feasibility, tend to a decreased process robustness. Small variations in material properties or increasing tool temperatures can lead to a defect part. To estimate the robustness the Cpk-value can be evaluated for each criterion based on the metamodels. Generating simulation values by using the metamodels is a very cheap computation, hence 100 000 points are tested with user-defined distribution functions (Table 2 with normal distribution), nominal values and variation range of the disturbance variables (see Table 2). In order to get one global and part specific robustness value, the ppm (parts per million) value is used. Thus, all points located outside of the valid process window generate a defect part.

| Table 2: Estimation of process capability and robustness based on metamodels |
|---------------------------------|----------------|----------------|
| Parameter | Nominal | $\sigma$ | Q.-Crit. | Cpk | PPM |
| Friction $\mu$ | 0.07 | 0.01 | Thinning 1 | 0.728 | 28 910 |
| Tool temperature $T$ | 30°C | 5°C | Thinning 2 | 1.076 | 1 250 |
| R-values $r_0, r_{45}, r_{90}$ | From exp. | 10 % | Wrinkles | 0.446 | 181 260 |
| Blank thickness $t_{\text{blank}}$ | 0.8 mm | 0.01 mm | Total | 210 170 |
The variation range of the disturbance variables in Table 2 represent the expected fluctuations during a normal serial pressing. The presented kitchen sink with the three previously defined quality criteria is not robust, because based on the metamodels a reject rate of about 21% is estimated. Thus, process control could possibly compensate changing material properties, tool temperature and friction conditions and consequently reduce the reject rate.

In case the process is robust enough or rather the part quality is not affected by disturbances, a process control is superfluous.

5. Evaluate observability

The observability presented in this paper is a measure to estimate whether a specific quality criterion can be predicted only by knowing the actual draw-in at the measured positions. A good observability of the quality criteria means that the part quality is fulfilled, as long as the target draw-in is reached. Thus, a changing part quality is reflected in the draw-in, which is essential for the subsequent process control.

It is evaluated based on a new approach, which is depicted in Figure 3. In a first step, the quality criteria and draw-in values are normalised to mean value 0 and standard deviation 1. Thus, sensitivities are comparable and the deviations in the leave-one-out cross validation are independent of the level of the quality criteria. Then the root mean squared error (deviations to the simulation values) is subtracted from 1. Consequently the observability reaches 100%, if no error occurs in the leave-one-out cross validation. An error of one standard deviation in the cross validation leads to an observability of zero (not observable). The observability coefficients for the defined quality criteria and draw-in sensors defined in Figure 3 are shown in Table 3.

![Figure 3: Evaluation of observability](image)

**Table 3: Observability coefficients**

<table>
<thead>
<tr>
<th>Quality criterion</th>
<th>Observability with…</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>draw-in, tBlank</td>
</tr>
<tr>
<td></td>
<td>draw-in, tBlank</td>
</tr>
<tr>
<td>Thinning 1</td>
<td>0.952</td>
</tr>
<tr>
<td>Thinning 2</td>
<td>0.936</td>
</tr>
<tr>
<td>Wrinkles</td>
<td>0.614</td>
</tr>
</tbody>
</table>

Furthermore, additional sensors such as an eddy-current system (see [9]) and a measurement system for the initial blank thickness, can be added to the draw-in signals to provide different information and thus to possibly enhance observability. If the observability does not change significantly with the added sensors, then the effect of the measured variable is already reflected in the draw-in. This can be seen for the thinning criteria in Table 3. On the contrary, the observability of the wrinkle criterion can be increased by providing additional information about the R-values with an eddy-current system and the blank thickness with laser sensors. An observability coefficient of 0.7 is classified to be sufficient, which corresponds to an error of 0.3σ. Thus, additional measurements beside the draw-in can provide relevant information in order to increase observability.

6. Evaluate controllability

The definition of controllability in this manuscript is understood as the ability to influence the draw-in by variation of the control variables, whereby disturbances are taken into account. First, each draw-in measurement is analysed individually if the target draw-in can be reached and which control variable should be adjusted. In a second step a metamodel-based process simulation with user-defined disturbances is computed. Thereby all control variables are optimised in order to reach the defined target draw-in at the determined positions.

6.1. Controllability of one draw-in position

The influences of the control and disturbance variables on the draw-in are analysed separately. The control variables are classified in different categories: insufficiently sensitive (red), sensitive enough
(green) and too sensitive (blue). Because of the nonlinearities in the metamodels, the slope of the metamodel changes over the level of the variable. The minimum / maximum slope or rather influence limit is thus not a fixed limit but is visualised as a range (orange / light blue), which corresponds to the standard deviation of the limit variation. Figure 4 shows on the left side the influences of the control variables exemplarily on the draw-in S06. The binder force $F_G^{(A)}$ is an inadequate control variable regarding S06 because of insufficient sensitivity. Whereas the force distribution is too sensitive on S06 for high forces on die cushion 3, thus small changes in the die cushion 3 force can lead to a jump in the draw-in. The other two control variables (blank position and binder force B) lead to a better response behaviour.

The disturbance variables are also classified in different categories: can be compensated (green), compensation dependent of other variables (orange) and cannot be compensated (red). Thereby many different combinations of disturbance variables are tested if the control variables are able to compensate the draw-in difference from the disturbance variables based on an optimiser. For the draw-in S06 with the target value 63 mm from nominal simulation (Figure 4, centre) all combinations of disturbance variables can be compensated by adjusting the control variables in the defined variation range. If the target draw-in is set to 83 mm instead (Figure 4, right), high friction values cannot be compensated. For this purpose the control variables should be reduced even more than the simulated range to reach the target draw-in.

6.2. Virtual process control with optimiser

The draw-in positions are analysed separately according to the methods presented in the previous chapter 6.1. In order to verify if due to disturbance variables still all target draw-in values can be reached simultaneously by adjusting the control variables, a process simulation is computed with variations between every press stroke (see Figure 5).

**Figure 4:** Influence of control and disturbance variables on draw-in S06

**Figure 5:** Metamodel-based process simulation to verify controllability of draw-in
The diagram at top left in Figure 5 shows the disturbance variables over the first 20 press strokes, which simulates the heating of the tools at the beginning of the serial pressing. For the normalised values 0 corresponds to the minimum and 1 to the maximum (see Table 1). The influence on the draw-in without control is depicted at top right in Figure 5. At the beginning with small friction and cold tools the draw-in is much higher than it should be. After 10 parts the nominal simulation is reached, thus no deviations occur. The higher the friction and temperature get, the smaller the draw-in becomes.

By using an optimiser the control variables are automatically adjusted to the best combination in order to reach the target values of the six draw-in positions. At the beginning of a batch with low friction values the press forces are increased to the maximum (Figure 5, bottom left). The optimiser tries to find the optimal solution for all draw-in at the same time. Thus the blank position and force distribution are adjusted to reduce the global draw-in deviations, which is a maximum of 2 mm. After the third part the press forces are systematically reduced in order to meet all target draw-in. Until the 18th part all deviations are below 0.5 mm. The last two parts show again a larger divergence because the press forces are already reduced to the minimum of the variation range.

Even though all disturbances on draw-in S06 can be compensated individually (see Figure 4, centre), it is not possible to meet all target draw-in within the computed variation range of the control variables. Therefore the variation range should be increased.

7. Conclusion

The presented methodological approach shows a possibility to design and verify the feasibility of process control based on draw-in measurements. The approach is based on variant simulations, which are condensed to metamodels. The method delivers draw-in measurement positions and quantifies the capability to observe the quality criteria and thus the process based on the draw-in positions. Furthermore the effectiveness of additional sensors, such as an eddy-current system or measurement of blank thickness, in order to increase observability of the process can be analysed. Also the ability to influence the draw-in by adjusting control variables in case of any combination of disturbance variables is verified. In a final stage a production scenario, such as the start of serial pressing where friction and tool temperature increase, is simulated based on the metamodels. Thereby it can be verified whether all target draw-in can be reached at the same time.

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