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# Feedback control in deep drawing based on experimental datasets

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**Abstract.** In large-scale production of deep drawing parts, like in automotive industry, the effects of scattering material properties as well as warming of the tools have a significant impact on the drawing result. In the scope of the work, an approach is presented to minimize the influence of these effects on part quality by optically measuring the draw-in of each part and adjusting the settings of the press to keep the strain distribution, which is represented by the draw-in, inside a certain limit. For the design of the control algorithm, a design of experiments for in-line tests is used to quantify the influence of the blank holder force as well as the force distribution on the draw-in. The results of this experimental dataset are used to model the process behavior. Based on this model, a feedback control loop is designed. Finally, the performance of the control algorithm is validated in the production line.

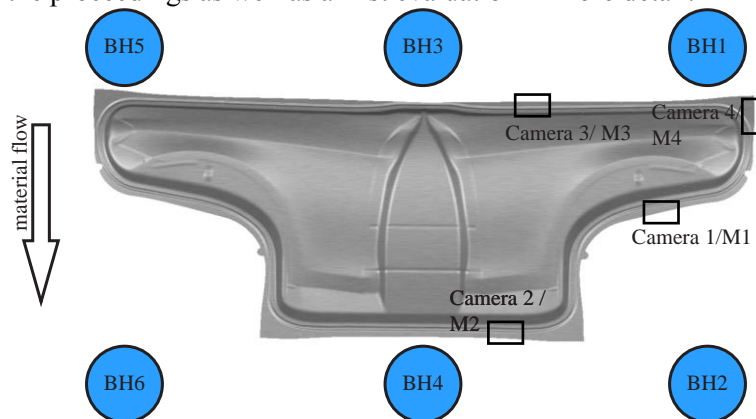
## 1. Introduction

In series production like the production of car body parts, the tool design aims for a large process window. Different methods have been developed in the past to design the tool for this purpose. Beside the methods used in research [1][2], also software companies like AutoForm offer software tools for robust process optimizations. Despite the effort to achieve a large process window, the design of the part itself leads to a small window. With the small working window, the process is highly influenced by process noise like the temperature increase in the tool or scattering material properties. A high sensitivity for the tool temperature leads to a high number of adjustments during the production of a single batch, as it can be seen in the paper of Hortig [3]. Also the coil to coil variation as well as the variation inside a single coil [4] can change the processing behaviour significantly and lead in combination with the small process window to an increased scrap rate. As the part quality is usually only checked at the end of a press line, a large number of parts is produced without even realising the drop in quality, therefore an inline measurement system is needed. In the present paper, an optical draw-in measurement system is used to measure the draw-in as the draw-in at certain points has a high correlation with the strain distribution inside the part and can therefore be used as quality measurement. With having a quantifiable quality measurement, the system can be extended from purely informing the user about a quality drop to an automatically reaction on the drop. With measurements inside and outside the processing window, a dataset can be generated to model the process. Based on these models, a feedback control loop is designed and later on validated in the production line.



## 2. Experimental dataset

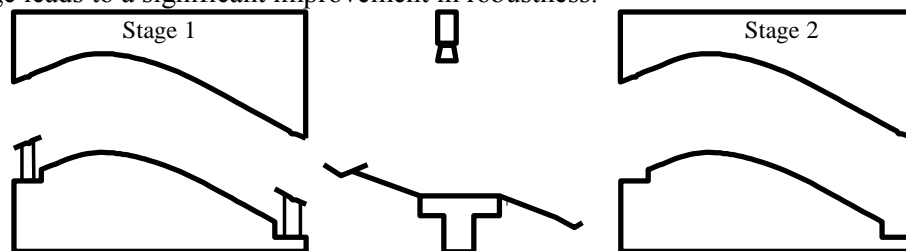
The first step in designing the control algorithm is the determination of an appropriate model for the process for virtual tests of the control algorithm. For the presented paper, the modelling and control approach is demonstrated on a front fender. For the dataset the forces of the different blank holder cylinders (BH) are adjusted to see the reactions of the part regarding the blank holder forces. The position of the cylinders as well as the part itself can be seen in figure 1. The following subsections describe the setup, the proceedings as well as a first evaluation in more detail.



**Figure 1.** Blank holder and measurement positions

### 2.1. Experimental setup

For a feedback control it is necessary to have the measurement as close as possible to the actuated stage to avoid unnecessary dead times which would decrease the performance of the control algorithm. Therefore the cameras for the optical measurement system are placed over the positioning stage between the first and second drawing stage as it can be seen in figure 2. As the part is symmetric and as the tryout of the tool did not produce any asymmetries, only the draw-in of the right fender is measured. The approximated field of view of the four cameras is shown in figure 1. Each camera image results in one measuring point (M) called according to the camera number. As the measurement system provided by VMT Bildverarbeitungssysteme GmbH is based on edge detection algorithms, the distance between the edge of the blank and a feature which can be detected as edge is measured and taken as measuring value. As in car body fabrication nearly all of the drawing is down in the first stage, monitoring and controlling the first stage leads to a significant improvement in robustness.

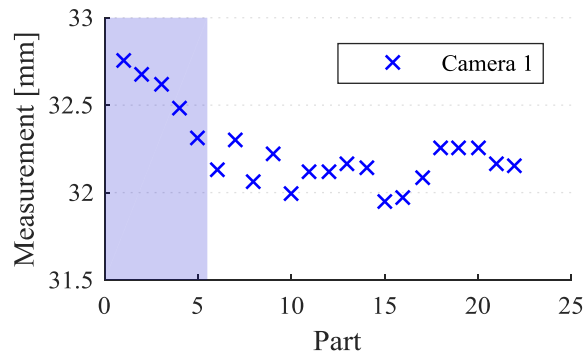


**Figure 2.** Position of optical measurement system

### 2.2. Proceedings for experiment

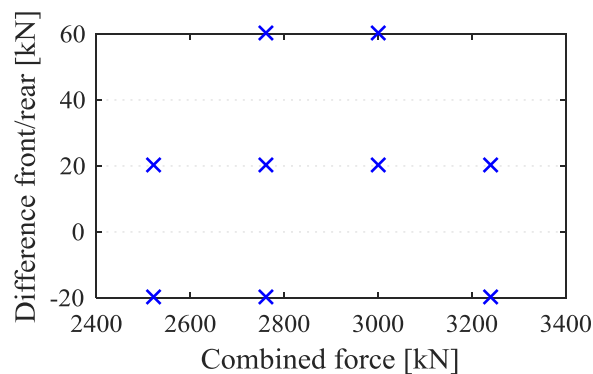
For generating a homogeneous data set, it is necessary to keep all non-varied parameter as constant as possible during the experiments. As tool temperature could significantly influence the outcome of the experiments, the tools are heated up to a constant temperature by producing over 200 parts. For each selected data point approximately 20 parts are made to have a large enough data set at the operating point, as well as to determine the part quality at the end of the production line. The necessity of a larger number of parts can also be seen in figure 3 which shows the fluctuation of the draw-in of a single data point. The part in the diagram with the blue background clearly shows the start-up unsteadiness of the

draw-in during the start-up phase of the mechanical press and is therefore not considered for the data set.



**Figure 3.** Fluctuation of measurement of camera 1

For the generation of the dataset the variations of the blank holder forces are cut down to two different types of variations and their combinations. First of all the combined force of the blank holder is varied and second the difference between one front cylinder and its rear counterpart (e.g. BH1 and BH2), while the front rear difference is the same for all three cylinder pairs. As the data set is used for modelling the process, the number of data points has to be large enough to allow for complex models. Originally twelve data points should be evaluated but due to material and issues as well as unreachability (due to cracks) or implausibility of results only the nine points shown in figure 4 are used for the dataset.



**Figure 4.** Data set

### 2.3. Evaluation of the dataset

For every data point in the set, the measurement values of the draw-in after the start-up phase is averaged and the standard deviation over the measurements for one point is determined. These values as well as the difference between the largest and the smallest measurement over all data points can be seen in table 1. As in feedback control, the difference between the reference value and the current value is taken, a low standard variation for similar parts is needed and therefore the measuring point M2 seems too instable for a robust control. The other three points on the other hand seem to be in acceptable range for feedback control with the fact in mind that the material inside a coil does not change significantly during the 20 produced parts for every point.

After evaluating the quality of the measurement, the dependency between the input parameters and the measurements has to be evaluated. As the variation range of the input parameters is relatively low and therefore the influences might be linear, the analysis using Pearson correlation coefficients is sufficient before modelling the process. The correlation coefficients, also provided in table 1, show that measuring point M4 is mainly influenced by the combined force, while the points M1 and M2 are mainly depending on the difference between the front and rear cylinders. Measuring point M3 is influenced by

both input variations. As all measuring points have some correlation with the input parameters, the measurements show the state of the part.

**Table 1.** Analysis of data set

	M1	M2	M3	M4
Correlation combined force [-]	-0.33	-0.34	0.74	0.93
Correlation difference front/rear [-]	0.64	0.55	-0.49	-0.12
Difference between min and max value [mm]	1.34	4.13	1.93	1.39
Mean standard deviation [mm]	0.19	0.59	0.18	0.23

### 3. Modelling of the process

For the usage of the dataset in the design of a control algorithm, an appropriate model for the data set has to be determined. Two different types of models are evaluated in this process. The first type is regression based models and the second type is based on radial basis functions. The quality of the regression models is determined by their fitting accuracy  $R^2$  and their prediction capability  $R^2_{\text{prediction}}$  [5], while the quality of the radial basis functions can be determined by cross validation. As all regression models have a fitting accuracy close to one (table 2), the radial basis functions were neglected. Calculating  $R^2_{\text{prediction}}$  on the other hand shows that the models for M1 and M2 are heavily influenced by single points and therefore have a  $R^2_{\text{prediction}}$  value close to zero. Based on these models, the control algorithm can be designed.

**Table 2.** Analysis of data set

	M1	M2	M3	M4
Model type	quadratic+interaction	quadratic	quadratic+interaction	quadratic
$R^2$ [-]	0.92	0.86	0.99	0.97
$R^2_{\text{prediction}}$ [-]	0.23	0.07	0.88	0.8

### 4. Design of the control algorithm

The aim in the design of the algorithm is a comprehensive behaviour and therefore the control changes in the output should be assignable to changes in the inputs. Four inputs (M1-M4) and two outputs ( $F_{\text{comb}}$  and  $F_{f/r}$ ) would result in a complicated MIMO (Multiple Input –Multiple Output) application as all inputs influence all outputs. The first step in designing the control algorithm is a decoupling of the different effects. As M4 is nearly uncorrelated to  $F_{f/r}$ , the influence of  $F_{f/r}$  on M4 can be neglected and M4 is only used for the correction of the combined force. Since only the model for M3 has a good predictive capability, it is used for the adjustment of the difference between the front and the rear cylinders.  $R^2$  of linear models for M3 and M4 is already between 0.85 and 0.9, therefore the regression coefficients ( $\beta$ ) of the linear models can be used in the control algorithm, resulting in the following control outputs.

$$\Delta F_{\text{comb}} = K * \frac{\Delta M_4}{\beta_{F_{\text{comb}}}}$$

$$\Delta F_{f/r} = K * \frac{-\Delta M_3 - \beta_{F_{\text{comb}}} * \Delta F_{\text{comb}}}{\beta_{F_{f/r}}}$$

As M3 is highly correlated to  $F_{\text{comb}}$  and  $F_{f/r}$ , the influence of a change in  $F_{\text{comb}}$  on M3 has to be considered for the calculating of the correction of  $F_{f/r}$ . In the aim of accounting for errors through the usage of linear models, a gain K is introduced as tuning parameter. The effect of the gain can be seen in the following section.

## 5. Virtual performance analysis

The controller design is evaluated in a Simulink model where the first part is drawn with a starting point that differs from the reference point. For the calculation of the draw-in the models from section 3 are used. With the difference between the models for calculation and the models inside the control algorithm kind of a modelling error is already introduced. The reference point lies at  $F_{\text{comb}}=2760$  kN and  $F_{f/r}=20$  kN, while the shifted starting point has the values  $F_{\text{comb}}=2520$  kN and  $F_{f/r}=60$  kN. Figure 5 with the gain  $K=1$  shows that the controller responds with a huge overshoot due to the quadratic influences in the models for the draw-in. To reduce the overshoot, the gain is adjusted so that the number of parts, until the reference is reached, is kept by five parts, but the overshoot in the first control reaction is reduced. The final result can be seen in figure 6 where the overshoot is close to or less than a millimetre in the draw-in. With these parameters set, the control algorithm can be evaluated in the production line.

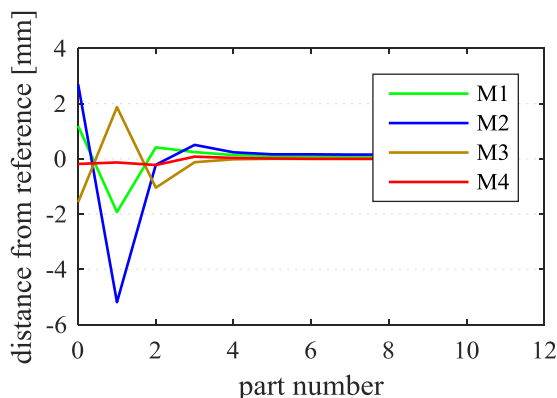


Figure 5. Gain  $K=1$

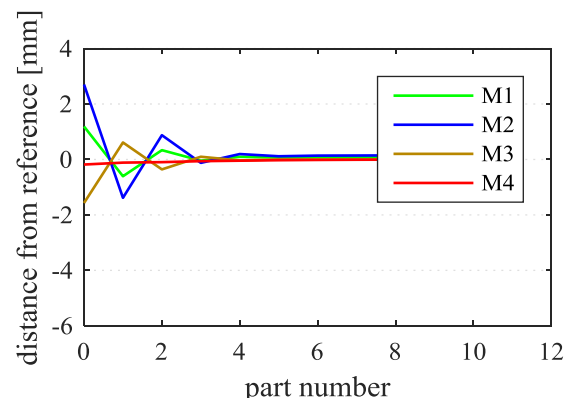


Figure 6. Gain  $K=0.7$

## 6. Performance check in production line

For the validation of the proposed control algorithm two different scenarios are tested. The first scenario is the start from a shifted starting point for example when the last batch had different material properties, while the second scenario is a change in tribology. As the control is not implemented in the press line, the procedure for testing is similar to the generation of the data set. For every setting of the press around 20 parts are manufactured and the average of the last five parts is taken as control input.

The results for the shifted starting point can be seen in table 3. As the deviation in M4 is close to zero, the first control intervention only corrects the force distribution, while the second control intervention partly corrects the combined force. A third control intervention would focus on the combined force, as the deviation of M3 is close to zero. The improvement through control can be seen in M1, M3, and M4 as the deviation to the reference is lower than the standard deviations of the measurements themselves. The values of M2 are deviating due to an unknown reason, but the reliability of M2 is quite bad as the standard deviation of M2 is three times higher than the other sensors. Therefore the control system works properly for this case.

Table 3. Shifted starting point

Combined force [kN]	Difference f/r [kN]	$\Delta M1$ [mm]	$\Delta M2$ [mm]	$\Delta M3$ [mm]	$\Delta M4$ [mm]
2880	-60	-0.846	-0.746	0.912	0.046
2880	0	-0.260	0.354	0.304	0.114
2835	15	-0.054	0.988	0.07	0.108

**Table 4.** Increased lubrication

Combined force [kN]	Difference f/r [kN]	$\Delta M1$ [mm]	$\Delta M2$ [mm]	$\Delta M3$ [mm]	$\Delta M4$ [mm]
2760	20	-1.304	2.264	-2.96	-2.182
3660	-30	-2.406	1.586	-1.142	0.116
3610	-115				

In the acquisition of the model for the draw-ins, the influence of friction is neglected, as the lubrication stays constant. For testing the robustness of the control with some kind of process noise the lubrication of the upper side of the blank is raised by 14% and the lubrication on the lower side by 36%. These lubrication changes lead to a significant change of the draw-in in all directions. While the deviation in the direction of M4 can be nearly compensated in one step, the distribution of the force related values still show a significant deviation. This deviation might only be compensated in M3 while the positive correlation between M1 and  $F_{fr}$  would lead to a further deviation in this point. This allows the conclusion that the control is able to compensate for changes in the used measuring points, but is unable to improve the overall part quality when the friction changes significantly.

## 7. Conclusion

The proposed approach for a feedback control based on an experimental dataset works when the process behaviour does not change significantly (e.g. lubrication change by 30% is too high). As only the dataset is generated with material of the same coil, the influence of the material properties on the results can be neglected, as the results in table 3 show. All in all feedback control based on optical draw-in measurements after the first drawing stage can be used to improve the robustness of the forming process.

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