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Evaluation of control strategies in forming processes

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Abstract. Products of forming processes are subject to quality fluctuations due to uncertainty in semi-finished part properties as well as process conditions and environment. An approach to cope with these uncertainties is the implementation of a closed-loop control taking into account the actual product properties measured by sensors or estimated by a mathematical process model. Both methods of uncertainty control trade off with a financial effort. In case of sensor integration the effort is the cost of the sensor including signal processing as well as the design and manufacturing effort for integration. In case of an estimation model the effort is mainly determined by the time and knowledge needed to derive the model, identify the parameters and implement the model into the PLC. The risk of mismatch between model and reality as well as the risk of wrong parameter identification can be assumed as additional uncertainty (model uncertainty). This paper evaluates controlled and additional uncertainty by taking into account process boundary conditions like the degree of fluctuations in semi-finished part properties. The proposed evaluation is demonstrated by the analysis of exemplary processes.

1. Introduction

Despite the awareness of fluctuations influencing the results of forming processes, the approach in industrial reality is the use of inflexible production facilities. In result, there is little possibility to react to the fluctuations. The adjustment procedure is usually passive, which means that the operator has to react to poor product quality by stopping the production and by manually adjusting set-screws in the tools. All parts that have been produced before the operator reacts do not meet the geometric specification and are rejected into waste.

The result of this procedure is that the scrap rate depends on the uncertainty in the influencing factors. Apparent influencing factors on resulting product geometry are, e.g. properties of the semi-finished parts, like geometry and yield stress [1] or environmental factors like temperature and incident solar radiation. But there can also be unknown influences, whose effect on the part quality cannot be determined [2]. If the adjustment procedure is human-induced, part quality and scrap rate also depend on the skills of the operator. It is obvious that the implementation of a closed-loop control system can help to improve process stability batch-wide and reduce set-up times for one tool or batch.

Even though methods of control theory have improved many consumer products in the past years, they have not been applied to many forming processes at the level of controlling actual part properties.

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This is caused by the challenges when measuring actual part properties as well as a lack of appropriate actors to manipulate these. Furthermore, modelling the whole production system, process and part behaviour, which would be necessary to apply classical methods of control theory, is hardly possible because of non-linear and often non-deterministic behaviour of the components. Additionally, there are some impediments in industrial practice, which complicate the implementation of process control systems in the production environment. Besides the additional effort for developing and setting up hardware and software, the risk of system failure may increase because of the increased complexity of the components. At last, there can be an increase of cycle and changeover time and thus a decrease of productivity.

This paper provides an approach to support the process engineer during the development of a process control system when choosing appropriate sensors and control structures. When measuring product properties in the production, there is a trade-off between effort and degree of interest of the measured signal. The deeper the sensor is integrated into the process and the closer located to the controlled variable, the higher is the effort to integrate the sensor. Variables further away from the forming zone can usually be measured easier, but the correlation to the controlled variable has to be determined in order to estimate the variable from the measured signal [3]. Besides, many control approaches are based on an iterative procedure, leading to an increase of precision but also to a decrease in the output rate of the process.

Summing up, there is a magic triangle of the opposing aims “quality”, “productivity” and “effort” which the developer has to deal with. The following describes how to find a trade-off between these aims under certain constraints with the help of a systematic approach, validated by three process examples from the field of bending.

2. Systematic approach for control development

Before discussing the criteria for sensor and model selection, an overview on possible sensor configurations and the effect on the integration effort and the type of process model is given.

There is one major challenge to be managed when measuring product properties in forming technology: properties relevant for the quality of the finished part are usually hard to measure during the process. This is caused by poor accessibility of the forming tools and by the fact that many relevant properties are subject to a recovery process subsequent to the forming process. Altogether, there is an increased effort when measuring close to the product and during the process compared to measuring machine properties or taking the part off the process and performing an offline measurement [3].

Considerable measurement positions and chronologies are visualized in Fig. 1. The diagram is based on the process model proposed by [4] and [5] and describes the path of a product during production. The semi-finished part runs through the actual forming process, ending as in-process part. The subsequent recovery phase includes undesired effects resulting from unloading and removing the part. Properties of the final product are measured by the relevant quality criteria. Accordingly, they can only be determined after production. The signal labelled “online measurement” includes all properties of the part which can be measured during the process and are used to estimate or predict product properties by the “adaptive process model”. By comparing the model output labelled “estimated value” with an offline measured value, the process model is adapted. The estimated output value serves as substitute for a real measurement value and is compared with the set-point value as input of the “product property controller”. The output of this controller serves as set-point value for the inner loop controlling tool and machine. The actual state of tool and machine are additionally fed into the adaptive process model for estimation enhancement.

The structure described above represents possible signal flows considered. Depending on the sensor availability, some of the signals can be considered as optional. Some of the examples work without online measurement of part properties or without in-process tool and machine states. The calculation

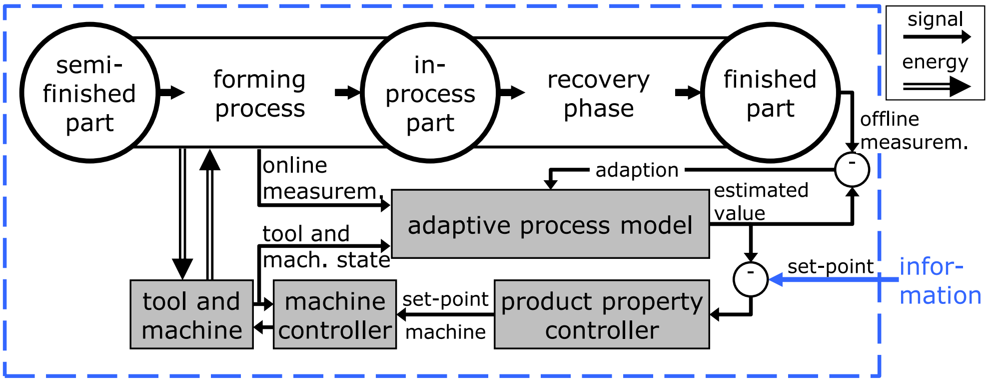

Figure 1. Structure of process, equipment and controller interaction.

rule applied by the adaptive process model depends on the available signals as well as the knowledge of process and machine behaviour. A lack of appropriate sensor signals and knowledge results in a higher model uncertainty in the adaptive process model and thus, in a higher uncertainty in the estimated value.

The trade-off between the effort for sensor integration and the described uncertainty is a major challenge during control development for forming processes. The expected fluctuations in the properties of the semi-finished part can be considered as one indication. Besides, an economic indication can be the scrap cost per part, which indicates the relevance of scrap parts.

The higher the fluctuations in semi-finished part properties and the higher the scrap cost per part, the higher is the necessity for individual part control. If the semi-finished part properties within one batch are slowly changing and scrap costs are low, a feed-forward control with offline measurement and adaption is suitable because the overall scrap costs are tolerable.

On the other hand, in case of expensive parts with indeterministic behaviour, an online measurement with adaption to each individual part is proposed.On the basis of this pre-selection, the sensors which can be integrated have to be determined. The design of the model depends on the availability of information about the relationships between input and output signals. If possible, analytical or empirical descriptions are aspired. If these cannot be achieved, black-box models can be taken into charge, if sufficient data for teaching the model is available, for example from experiments or simulation.

The examples considered in the following section demonstrate the benefit of different control strategies for given combinations of property fluctuations and scrap costs.

3. Process examples

Four process configurations from the field of bending are analysed concerning the three criteria “quality”, “productivity” and “effort”. Quality describes the actual process output compared to a tolerance specification given by the product design. It is quantified by the ratio of the number of parts meeting the specification over the total number of parts in a batch. The value for productivity is rated by the average number of parts produced with one press stroke, which is a simplification excluding given performance characteristics of the production system. Finally, the effort is determined by the cost of the sensor, the time to integrate it into the tool system and to modify the surrounding in order to receive a high-quality signal in the control. Since the exact quantification of this value depends on the technologic and economic environment of the process, the evaluation is drawn on a qualitative basis.

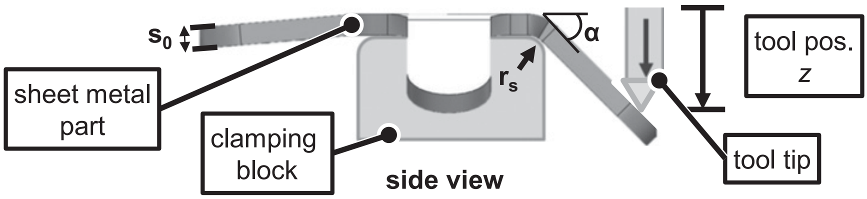

Figure 2. Free bending of a sheet metal part according to [3].

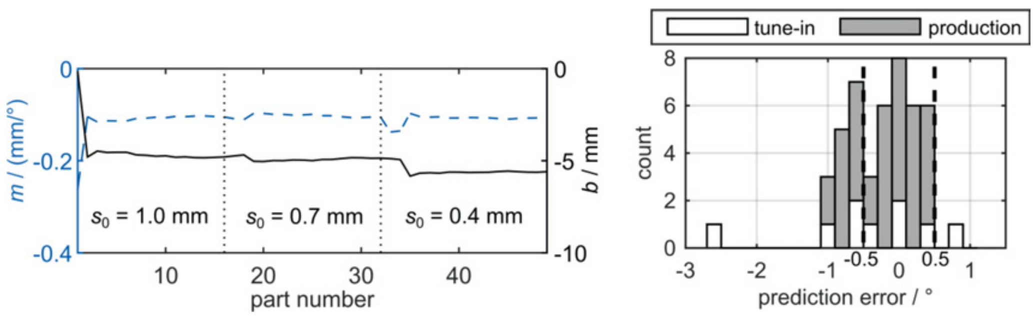

Figure 3. Left: regression parameters m (dashed) and b (solid); right: histogram of the resulting prediction error during tune-in and production phase.

3.1 Feed-forward controlled sheet bending

The first process example is a feed-forward controlled bending process with iterative part-to-part adaption as described in [3]. As illustrated in Fig. 2, a sheet metal part is mounted to a clamping block and bent to the angle α by the vertical motion of a tool tip.

Strategy 1 consists of a feed-forward model ($z = m\alpha + b$) which determines the necessary bottom dead centre position z of the press for a desired bending angle α. The actual bending angle is measured offline on a camera-based measuring station and is used to adapt the linear parameters m (gain) and b (offset) of the feed-forward controller by a recursive least squares algorithm. The evolution of the parameters is illustrated in Fig. 3 (left). It can be observed that the parameters tune in to a continuous state after a tune-in phase of 3 parts. Since the parameter adaption is continued during production, the algorithm can react to continuous changes in process conditions. The changes of sheet thickness s_0 after part 17 and 34 act as a step in disturbance and initiate a new tune-in phase.

A camera-based online measurement system offers the opportunity to control uncertainty in the machine behaviour, as demonstrated in control strategy 2. The structure of the control is similar to strategy 1, with the difference that the output of the feed-forward controller is the actual bending angle of the loaded in-process part instead of the press position. This in-process angle is fed to the inner loop of the machine control as set-point value.

strategy 1		
quality	**productivity**	**effort**
56%	1 part per stroke	low

strategy 2		
quality	**productivity**	**effort**
79%	1 part per stroke	medium

The evaluation of strategy 1 and 2 regarding the three criteria is summarised in the tables on the right. The assumed tolerance is $\pm 0.5°$ and the total number of parts produced is 52. For strategy 1 the ratio of in-tolerance parts over the total number of produced parts is relatively low, resulting from a wide fluctuation of the resulting angle (see Fig. 4 “strategy 1”). Besides the effect of uncertain properties of the semi-finished parts, the main effect on quality is the variation of machine and tool behaviour. The benefit of strategy 2 is a lower variation of the prediction error (see Fig. 4 “strategy 2”) and a higher quality value at the price of an increased effort for sensor integration.

3.2 Closed-loop controlled sheet bending

In order to furthermore increase the quality by eliminating the effect of material fluctuations, a closed-loop control structure is implemented. It uses the same online angle measurement as strategy 2 but involves several loading-unloading cycles to intermediately measure the angle of the unloaded part. The set-point angle for each stroke is determined by the process model by adding an estimated spring-back angle to thedesired angle of the finished product. After one loading-unloading cycle ($\triangleq$1 stroke), the real spring-back angle is measured and the estimation is adapted. This procedure is repeated until the resulting angle lies inside a small corridor.

The result can be seen in Fig. 4 (“strategy 3”). The probability density function is narrower than for the prior strategies, leading to an increase of the in-tolerance ratio. The disadvantage of this strategy is the decreased productivity, resulting from the multiple strokes necessary to produce one part.

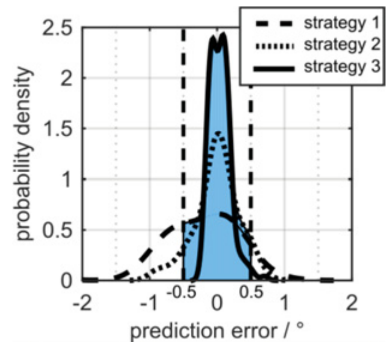

Figure 4. Prediction and results of offline and online measurement.

strategy 3		
quality	**productivity**	**effort**
99%	0.39 parts per stroke	medium

3.3 Bending with real-time adaptive feed-forward model

The fourth example is a three-point bending process of a beam-shaped part. The process configuration aims at coping with the shortcomings of strategy 1 to 3, which are low quality (strategy 1 and 2) and low productivity (strategy 3), provoked by an iterative bending strategy. In order to realise a process control model which adapts to the properties of each individual part, additional information about the semi-finished part has to be obtained. Besides the actual bending angle, one significant signal for the identification of spring-back behaviour is the forming force over angle curve. It is measured by a tool-integrated force sensor. Methods predicting spring-back during the loaded state of the part have been proposed before and are based on an elastic model [6, 7] that predicts the recovery phase. However, these methods cannot compensate variations in the elastic behaviour which leads to model errors.

A high uncertainty in yield force and varying part stiffness requires individual spring-back prediction. Figure 5 shows a method that identifies yield force and part stiffness in real-time and uses these parameters to predict spring-back during the loaded state. The prediction of the controlled variable during the process

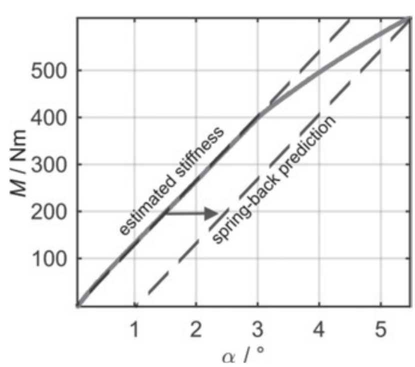

Figure 5. Spring-back prediction based on an elastic feed-forward model with online model identification.

enables a higher productivity. Furthermore, the real-time adaption of the elastic feed-forward model can compensate individual variations in part properties.

A comparison between a control strategy using a feed-forward model without a force sensor (strategy 2) and one using real-time adaption of the elastic feed-forward model with force sensor (strategy 4) is given in Fig. 6. It can be seen that an adaptive elastic model significantly increases the quality. On the downside, it requires a high effort for additional force sensor integration and for the implementation of the identification algorithms.

The process evaluation regarding the three criteria is summarised in the table on the right. The assumed tolerance is $\pm 0.5^\circ$ and the total number of parts produced is 22.

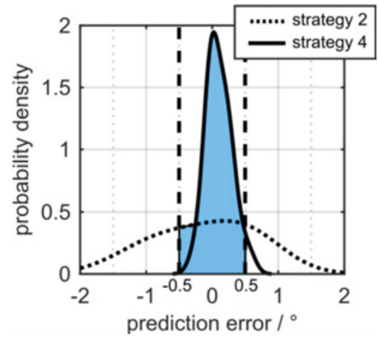

Figure 6. Comparison of different feed-forward models for spring-back prediction in cast aluminium parts.

strategy 4		
quality	**productivity**	**effort**
95%	1 part per stroke	high

4. Conclusion

The paper demonstrates an approach to cope with the trade-off between quality, productivity and effort that process engineers are confronted with when setting up a controlled forming process. Depending on the requirements on quality and productivity as well as the uncertainty in the properties of semi-finished parts, the approach starts with a low effort for sensor integration and includes a successive increase of sensor information fed to the model in order to increase quality and productivity.

Strategy 1 is only sufficient if tolerance specifications are low and fluctuations in semi-finished part properties are continuous. Strategy 2 controls uncertainty in machine behaviour but requires additional online sensors. Strategy 3 uses this configuration to nearly eliminate scrap at the price of low productivity, which is suitable for products with unknown properties, for example in prototype production. Finally, strategy 4 combines high quality and productivity by providing additional information to the process model but requires the highest effort for sensor integration. This strategy is suitable for mass production of high-value parts with strongly fluctuating properties, where each reject part implies a high economic disadvantage.

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