Data-driven inline optimization of the manufacturing process of car body parts

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Abstract. The manufacturing process of car body parts needs to be adaptable during production because of fluctuating variables; finding the most suitable settings is often expensive. The cause–effect relation between variables and process results is currently unknown; thus, any measure taken to adjust the process is necessarily subjective and dependent on operator experience. To investigate the correlations involved, a data mining system that can detect influences and determine the quality of resulting parts is integrated into the series process. The collected data is used to analyze causes, predict defects, and optimize the overall process. In this paper, a data-driven method is proposed for the inline optimization of the manufacturing process of car body parts. The calculation of suitable settings to produce good parts is based on measurements of influencing variables, such as the characteristics of blanks. First, the available data are presented, and in the event of quality issues, current procedures are investigated. Thereafter, data mining techniques are applied to identify models that link occurring fluctuations and appropriate measures to adapt the process so that it addresses such fluctuations. Consequently, a method is derived for providing objective information on appropriate process parameters.

1. Introduction
The car body part production process is affected by several variables [1] that cause quality fluctuations. It faces major challenges in relation to decreasing process windows and lot sizes. When a quality defect appears, the process needs to be manually adjusted using control variables until parts of acceptable quality are produced. The search for suitable settings often results in significant downtime. Improving the strategy for identifying settings would therefore offer a potential increase in stamping plant productivity.

The current problems are related to a lack of knowledge about influential factors and existing correlations in the overall process. Digitization in the context of the so-called “industry 4.0” offers the potential to solve these problems. One aspect of this digitization involves the automatic exchange of information between machines and products, which creates production processes that continuously produce large amounts of data [2]. The analysis of this data enables the understanding and the modeling of complex relations. Results that until now have appeared to be random can be predicted, and measures that have depended on intuition and operator experience can be determined based on
these relations. Consequently, defects can be prevented and time needed for trial and error efforts can be reduced considerably.

A method for predicting defects was previously created by Purr et al. [3]. Now a method is presented that calculates objective recommendations for adapting the production process to avoid defects. The determination of these recommendations is based on influences and relations derived from measured and collected data using data analysis and learning algorithms.

2. Available Data

The proposed method is based on the analysis of data generated during series production in stamping plants. To acquire the data, a system was developed that documents uncontrollable influences, process parameters and process results for each car body part. This system was integrated in a BMW stamping plant. Details on the data acquisition system have been published in [4]. To track and trace parts, each blank is labelled by a laser marking unit. A component thus gets a unique identity to which the acquired data is assigned. As a result, the system generates a feature vector, $f(i)$, for each produced component, $i$, which includes the material properties, $m(i)$, control variables during processing, $c(i)$, and an associated description of the part quality, $q(i)$. Definition (1) shows the structure of a feature vector $f(i)$. When considering the system for “producing a car body part,” $m(i)$ and $c(i)$ contain the input variables, and the elements of $q(i)$ are the output variables. The quantities of $c(i)$ can be controlled and set during production. Material properties $m(i)$ cannot be influenced during series production. It has to be mentioned that unlike all other variables, quality data $q(i)$ is manually recorded. It is therefore not available for each part.

$$f(i) = \begin{bmatrix} m(i) \\ c(i) \\ q(i) \end{bmatrix}$$ (1)

The material properties vector $m(i)$ consists of measured values that describe the characteristics of blanks as precisely as possible. These variables are determined during the blank cutting step and are assigned to the appropriate part. The elements of $m(i)$ are partially vectors themselves. The structure of $m(i)$ is defined in (2). The value $s(i)$ is an indicator of the strength of a blank, $p(i)$ and $u(i)$ provide roughness parameters, $R_a$ and $R_{pc}$, in five tracks in a transverse manner to the strip running direction. $o_{s_{top}}(i)$ and $o_{s_{bottom}}(i)$ specify the amount of lubricant in 20 tracks across the strip on the top and bottom side respectively. In addition to the measured oil amount of the single tracks, their average and standard deviation are calculated to describe the overall oil layer. The variable $d(i)$ includes three thickness measures transverse to the strip running direction.

$$m(i) = \begin{bmatrix} s(i) \\ p(i) \\ u(i) \\ o_{s_{top}}(i) \\ o_{s_{bottom}}(i) \\ d(i) \end{bmatrix} = \begin{bmatrix} s(i) \\ Ra_{s_{top}}(i) ,..., Ra_{s_{top}}(i) \\ R_{pc_{s_{top}}}(i) ,..., R_{pc_{s_{top}}}(i) \\ Ra_{s_{bottom}}(i) ,..., Ra_{s_{bottom}}(i) \\ R_{pc_{s_{bottom}}}(i) ,..., R_{pc_{s_{bottom}}}(i) \\ d_{s_{top}}(i) ,..., d_{s_{bottom}}(i) ,..., d_{s_{bottom}}(i) \end{bmatrix}$$ (2)

The vector of control variables $c(i)$ includes settings during part processing. Its structure is defined in (3). The control variables include the adjustment of a drawing cushion, $bf(i)$, setting of an oiling machine, $ro(i)$, and setting of blank holder spacers, $bs(i)$. In addition, other settings such as the stroke rate are summarized in the vector $os(i)$. Each setting contains multiple variables; for example, $bf(i)$ consists of the settings of six cylinders from the multipoint drawing cushion, and $ro(i)$ provides the spray pattern of the oiling machine, which consists of the settings of 40 valves on each side of a blank.
The vector $bd(i)$ includes the state of all existing spacers. The total number of spacers, $n$, depends on the tool used.

$$
\begin{bmatrix}
bf(i) \\
ro(i) \\
bs(i) \\
os(i)
\end{bmatrix} = \begin{bmatrix}
bf_{1}(i),...,bf_{80}(i) \\
ro_{valve1}(i),...,ro_{valve6}(i) \\
bs_{sp1}(i),...,bs_{sp22}(i) \\
stroke rate(i),...
\end{bmatrix}.
$$

3. Adjustment of the process to solve quality problems

3.1. Current procedure

When quality problems occur during series production, usually a readjustment of the process via control variables is required. Various options are available to adapt the forming process. The most important adjustment options are the blank holder forces, $bf(i)$, the setting of the oiling machine, $ro(i)$, and the setting of the blank holder spacers, $bs(i)$. Figure 1 shows the impact on the process of the three main settings in a simplified representation. The effect on the part is based mainly on the retention force for all settings. Mechanisms used to affect the quality of certain settings are described as follows:

- **Blank holder forces** determine the normal force acting on the flange of a metal sheet. Usually these forces are generated by an adjustable hydraulic multipoint drawing cushion. A value can be specified for each existing displacer cylinder, or at times a curve can be used.

- The **oiling machine** enables application of additional lubricant on the surface of the blanks. The valves of the oiling machine can be controlled separately. In consequence, lubricant can be selectively applied to critical part regions.

- The height of the **spacers** can be adjusted, which has an indirect effect on the normal forces via a force bypass. Therefore, spacers have a local impact on the material flow [5]. An increase in spacer height leads to a reduction in normal forces acting on a metal sheet.

However, no clear procedure is specified on how to use these mechanisms in the everyday activity of a stamping plant. When a quality problem occurs, the employees decide which and how existing parameters should be adjusted. This decision is based on individual experiences. Each plant operator has an approximate idea of the relation between the control variable adjustment and its effect on quality. Because of the subjective experience of each employee, which varies between individuals, in practice the adjustment procedure is not uniform.

The measures currently taken to fix quality problems during series production were recorded and analyzed to obtain an overview of the applied procedures. The production of 15,000 parts from multiple production lots were recorded. During the recording 25 quality problems occurred. Data were collected during different shifts with respect to the various parts. Figure 2 shows the relative frequency of usage as a first measure of the different control variables discussed above and the relative frequency of successful usage, where “successful” means that a quality problem was fixed after the adjustment.
All of the main variables were actively used. In addition, in some cases multiple variables were adjusted simultaneously. The blank holder forces were the most commonly used settings. In 48% of all cases the defects were fixed after an adjustment of the blank holder forces. Consequently, the blank holder forces are considered to be the most important setting used for process adjustment.

In summary, it was documented that many possible settings exist and that the procedures used when defects occur are diverse, although the settings have a similar effect. Reasons for the use of diverse procedures could be the varying experience of operators, a lack of procedural standardization, and a lack of knowledge about the exact effect of control variables. In addition, the settings of control variables are subject to restrictions and interactions; for example it is only possible to increase the amount of lubricant using the oiling machine (the amount of oil on a blank cannot be reduced). Currently the effectiveness of the different settings and influences is not documented.

3.2. Analysis of the effect of control variables

To overcome this lack of knowledge, the effect of the existing control variables is analyzed and a simplified conceptual model is developed to describe the relation between the condition of settings, \( c(i) \), and the quality of parts, \( q(i) \). The model is based on the physical effects of the settings described in section 3.1. Equation (4) shows this simplified model for the effect of the control variables:

\[
F_{\text{ret}} = F_{\text{others}} + F_{\text{friction}} = F_{\text{others}} + \mu F_N = F_{\text{others}} + \mu (F_{\text{total}} - F_{\text{spacers}}) = F_{\text{others}} + \mu (F_{\text{bf}} - D\Delta H) \tag{4}
\]

It is assumed that all settings shown in figure 1 primarily act on the retention force, and thus act on the material flow (see section 3.1). The model therefore describes the effect of each of the control variables on the retention force. It is expected that the material flow is proportional to the retention force, which is the sum of the friction force, \( F_{\text{friction}} \), and other forces such as the forming force produced by draw beads. Only the friction force can be controlled using the different settings introduced in section 3.1. The Coulomb friction law is the most suitable approach to describe the friction in the flange [6]. In the model, it is therefore assumed that the Coulomb friction law is valid and the friction force is the product of the normal force, \( F_N \), and the friction coefficient, \( \mu \). The local normal force is determined by the blank holder force, \( F_{\text{bf}} \), and the spacer force, \( F_{\text{spacers}} \), while the friction coefficient, \( \mu \), depends on the amount of lubricant and the material being processed. The spacer forces reduce the normal force, \( F_N \), depending on their set height. They are considered to be preloaded springs, and Hooke’s law is applied. The spacer force, \( F_{\text{spacers}} \), is thus a result of the product of the deflection, \( \Delta H \), and a spring constant, \( D \). The deflection of the spacer is also correlated with the thickness of the sheet [7], but this is not considered in this model. Adjustable variables in the model are: the blank holder force, \( F_{\text{bf}} \), the deflection of the spacers, \( \Delta H \); and the coefficient of friction, \( \mu \) (based on the amount of oil). These are underlined in (4).
According to the model, these settings should linearly affect the retention force and material flow. The conceptual model was validated by an experiment wherein parts were produced using different settings, and the effect of adjustments on the product was determined. One control variable was changed at a time, and the position of the impact lines resp. their distance to a reference was measured to quantify results. These lines result from the movement of the metal sheet under tensile stress over a tool edge [8]. The location of the impact line offers information about the material flow which is correlated with part quality [9].

To investigate the influence of control variables independently from the material properties, components with similar material properties, \( m(i) \), were chosen for the experiment. Interactions between different settings were not considered. In addition, the experiments were limited to typical settings used within a critical component region of a sample part. A possible influence of the component geometry on the local effect of the control variables is therefore not considered. In this case, a side frame of the current BMW X1 was regarded. The most critical region of the part is the C-pillar area. This is the area where most defects occur during series production.

Figure 3 shows the critical area of the example part, together with the settings that were changed during the experiment. Firstly, the pressure of cylinder 2 (the influence area of this cylinder on the part can be found in figure 3) of the drawing cushion was altered using steps documented during the investigations in 3.1, then the amount of additional oil in the marked region was altered, and finally the heights of three marked spacers were simultaneously varied.

![Figure 3. Setting area of the drawing cushion (left), setting region of the oiling machine (middle), and adjusted spacers (right).](image)

Through this the relation between control variables and material flow and the assumed linear correlations of the model were investigated. Figure 4 shows scatterplots of the correlation between settings and the location of the impact line. In all cases a linear correlation between the examined control variables and the material flow could be detected. The left scatterplot shows that a higher blank holder force results in a larger distance between the impact line and the reference; this indicates that the impact line is further outside of a component and that the material flow is lower. The middle plot shows that an increase in the amount of lubricant leads to a smaller distance and thus to an increased material flow, and the right plot indicates that the increase of the spacer height has an analogous effect on the material flow than better lubrication. The Pearson correlation coefficient between the adjustment value and the measured material flow is higher than 0.7 for each of the main control variables, and is therefore in the range of a strong linear relation [10]. It is evident that the influence of the control variables can be described using this simplified model with only a small error.
This experiment demonstrates that all control variables affect the retention force and therefore the material flow. In addition, the assumed linear relations are proven and the simplified model is validated in this respect. Based on these results, it can be assumed that the response of one control variable to quality problems would actually be sufficient in most cases and that the use of multiple settings is usually not necessary.

It is thus proposed that a main control variable should be defined and that the use of other variables should be prevented. Any effect reached by one control variable can also be reached by adjusting another one accordingly. Therefore the remainder of this paper focusses on developing a method to recommend the settings of one control variable. If a necessary adjustment is not possible due to restrictions, the model can be used to convert the measure to the setting of another control variable.

4. Data-driven inline optimization

4.1. Method

According to Bräunlich [11], it is always possible to adjust the manufacturing process of car body parts by altering the control variables to produce good parts. In practice, the difficulty lies in the identification of suitable measures. Using the results of 3.2 a method is proposed that efficiently determines the necessary adjustments of one control variable. Common optimization techniques for determining appropriate parameter settings would presuppose that the system behavior in the entire parameter space is described by a function [12]. If all variables of a feature vector \( f(i) \) are considered, this is not possible due to the high number of dimensions. Therefore a data-based method for calculating the appropriate settings is presented. The basic idea is that historical data can be used to extract direct connections and patterns between uncontrollable material properties, \( m(i) \), and the settings used for the production of good parts, \( c_{good}(i) \). Using these patterns and models, suitable parameters are calculated based on the properties of the incoming material. Figure 5 shows the basic principle of this concept. Since all main control variables affect the retention force and the blank holder force is the most commonly used one, the initial investigation is limited to the settings of the 6 cylinders of the drawing cushion. According to figure 6, the cylinder settings to produce good parts, \( bf_{good}(i) \), than are the output variables of the model.

![Figure 5](image1.png)  
**Figure 5.** Basic principle of the model to predict appropriate adjustments.

![Figure 6](image2.png)  
**Figure 6.** Structure of the model to predict the setting of the drawing cushion.
A description of part quality, $q(i)$, is not required in this method. The models are generated by application of learning algorithms to the data described in section 2. The multistage procedure for creating models to calculate handling instructions is defined in the following. This approach can be applied using different components and varying amounts of data.

4.1.1. Data Selection and Pre-processing
To train models, records are required that include the properties of the materials involved as well as the corresponding settings that produce good parts. As such, a matrix acquired in series production with part-specific information is used. The data sets $f(i)_{i=1,\ldots,z}$ include different settings of the blank holder force.

Since the process parameters are not adjusted for each of the $z$ produced parts, there are a smaller number of different settings than there are parts. Therefore, in the first step, the settings of the drawing cushion $bf(i)_{i=1,\ldots,z}$ are taken, and duplicate rows of the matrix are deleted. The result is the matrix $bf_{\text{unique}}(u)_{u=1,\ldots,y}$, which includes only $y$ unique settings of the drawing cushion. Unique control variable settings are then assigned to the parts that were processed using the respective control variable settings. This step results in groups of part records that have been produced with the same drawing cushion setting. Subsequently, the average material properties, $\bar{m}(u)$, are calculated for each of the unique settings $bf_{\text{unique}}(u)_{u=1,\ldots,y}$. The resulting dataset contains unique settings, together with the average properties of the blanks that have been processed with these settings. The number of parts, $n(u)$, processed using these settings is added as supplementary information. (5) defines the resultant matrix, $ru$.

$$ru = \begin{bmatrix}
bf_{\text{unique}}(u = 1) & \ldots & bf_{\text{unique}}(u = 1) & \bar{m}(u = 1) & n(u = 1) \\
\vdots & & \vdots & \vdots & \vdots \\
bf_{\text{unique}}(u = y) & \ldots & bf_{\text{unique}}(u = y) & \bar{m}(u = y) & n(u = y)
\end{bmatrix}$$

As the matrix should only include settings that lead to the production of good parts, rows that contain less than a specified minimum of parts ($n < \text{minimum}$) are removed, and the resulting matrix is labelled $ru_{\text{red}}$. It is assumed that settings used to produce only a few components have not led to the production of good parts. The remaining records are supposed to have led to the production of good parts. These assumptions are based on the current procedure in production where parameters are changed until good parts are produced again. This process leads to mistakes if there are small numbers of parts with very different characteristics $m(i)$. Due to the structure of the press line, after an adjustment, at least five press strokes are carried out until the measures are proved to be effective. The minimum $m$ is therefore set to five parts. For double parts the minimum is set to 10 records.

4.1.2. Data Analysis and Modelling
The data obtained in step a) can now be examined to determine correlations between the average material properties and the unique settings of the control variables. Therefore, a correlation analysis and visual examination are firstly performed; the results are the relations between single uncontrollable variables and single cylinder forces.

After identifying correlations, relations between the averaged uncontrollable input variables and each of control variables are modeled. The aim is not to interpret and explain, but to accurately forecast necessary adjustments. Modeling is always carried out with respect to the relation between at least one input variable and exactly one output variable/setting, and various algorithms are applied and evaluated. Examples include support vector machines, linear models, polynomial models, and neural networks.

4.1.3. Validation
The validation step is iteratively with the modeling step. If the validation result is not satisfying then it is necessary to repeat the modeling step to result in a better model. It is essential to prove that the model is able to generalize. To validate results, the available datasets of $ru_{\text{red}}$ are divided into training
and test data sets [13]; the records are split in a ratio of 2:1. The model is trained using the larger set, and it is then applied to both datasets. The correlation coefficient between the predicted and actual settings is then considered and scatterplots are used to compare the prediction with the reality. This allows an evaluation of model fitting to training data, as well as the model’s ability to generalize using test data. This process is repeated several times, each time with new divisions of the data. To avoid finding spurious correlations, the data is divided so that the training and test sets do not include data from the same production orders.

4.2. Experimental results
For validation, the proposed method is applied to the series process data from a data set involving the production of 52,753 bottom plates of a BMW 3 series sedan. These parts are manufactured as double parts side-by-side (two blanks per stroke). The objective was to derive models for predicting the appropriate adjustments of the drawing cushion. The pre-processing step resulted in a matrix, $ru_{\text{red}}(u)$, with 23 unique cylinder settings. Each of them was used for the production of at least 10 components (due to the double part manufacturing, the minimum is set to 10). Some settings were applied for the manufacture of several thousand components.

Through a correlation analysis of the matrix $ru_{\text{red}}$, several parameters were identified that show a correlation with the cylinder settings (figure 7 shows an excerpt from the correlation matrix). These correlations allow to derive tendencies. For example, a high correlation arises between the setting of cylinder 1, $b_{\text{cyl. 1}}(u)$, and the amount of lubricant at measuring track 7, $\sigma_{\text{top. track 7}}$. According to this correlation, the blank holder forces need to be increased with an increasing amount of lubricant in this area. According to Section 3 material flow rises with an increased amount of lubricant and this effect can be compensated by applying a higher blank holder force. The correlation can therefore be physically explained.

Figure 7. Extract from correlation matrix for matrix $ru_{\text{red}}$, with scatterplots, correlation coefficients, and frequency distribution.
A low correlation was found between the average blank thickness on track 2, \(\bar{d}_{\text{Track 2}}(u)\), and the setting of cylinder 1, \(bf_{\text{cyl.1}}(u)\). When the strip thickness is higher, the blank holder force settings tend to be lower. This is also explained using the conceptual model in Section 3. When there is an increase in the blank thickness there is a reduction in the deflection of the active blank holder spacer, \(\Delta H\). This reduces the fraction of the normal force derived from the spacer, and increases the fraction acting on the metal sheet. Consequently, a lower blank holder force is needed to achieve the same retention force. This physically explains the correlation.

After a manual search for correlations, models were developed that use several material properties to calculate the necessary adjustment of one cylinder of the drawing cushion. One model was derived for each of the six cylinders. In this case, the best-performing models were found to be support vector machines and linear models. From these, linear models were selected due to their simple functionality. Function (6) shows a linear model used to calculate the setting for cylinder 1 based on six \(m\) variables. The calculated coefficients and the selection of variables are not generally valid, and are re-established for other cylinders and components.

\[
bf_{\text{cyl.1,good}}(i) = C_1\delta(i) + C_2\sigma_{\text{average}}(i) + C_3\sigma_{\text{deviation}}(i) + C_4\sigma_{\text{track,1}}(i) + C_5\sigma_{\text{track,7}}(i) + C_6\sigma_{\text{track,2}}(i) + C_7
\]  

(6)

It was possible to derive six linear models to determine the required setting. Figure 8 shows the validation results for the example of cylinder 1, and figure 9 shows the results for cylinder 6; the Pearson correlation coefficients are higher than 0.7 for both the training and test data for both cylinders. A strong linear correlation [10] is thus proven between the predicted and actual settings used for both cylinders. For cylinder 1, the slopes of the trend line for the training data and test data are similar, which indicates that a quantitative forecast of the necessary adjustment could be possible. In contrast, the gradients at cylinder 6 are different for the test and training data, which indicates that only a qualitative recommendation can be calculated.

In conclusion, it is not yet possible to reliably calculate exact values. But the high correlations between suggestions and real settings indicate that tendencies can already be suggested with a high degree of certainty.

5. Conclusion
A method to provide process adjustments was developed and tested. To develop this method, current practices and the effect of control variables were investigated. A simple model that could be validated.
was introduced to describe the effect of control variables. Subsequently, a data-driven method to predict suitable settings was demonstrated. This method is based on the use of algorithms to generate models and patterns using historical data and their application to future data. To generate the models, a multi-step process has been defined which is applied to available series process data. The functionality of the proposed method was confirmed using a dataset containing more than 50,000 produced parts. The results prove that the suggestion and reality are well correlated and are already sufficient for qualitative recommendations. Considering that even historical data usually does not include ideal settings (settings are only changed after defects occur), these results are already very promising. In order to apply the model to upcoming new parts it will be mandatory to smoothen the input variables of the next stack of blanks. If a calculated measure cannot be carried out due to restrictions, it should be converted to an adjustment of another control variable. As shown in section 3 this is possible.

The success of this method depends on the nature of historical data. The forecast precision will be improved, when the uniformity and effectiveness of the procedure in the training data increases. Therefore, to improve predictions, it is necessary to specify the procedure accurately. Furthermore, to improve results, one control variable should always be preferred over the others during series production. If, other control variables are used instead of the preferred one within the training data, the measures are not considered by the model and accuracy is reduced. If the instructions calculated by this method (which are limited to one control variable) are followed and this data is used in future training, it is expected that predictions will automatically improve.

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