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A Classification-based Solution For Recommending Process Parameters of Production Processes Without Quality Measures

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Abstract

For production of sheet metal parts for car bodies, an adjustment of process parameters is required to maintain the desired part quality in presence of scattering blank properties. The digital transformation enables the application of data-driven methods for finding process parameters instead of a time-consuming experience-driven trial-and-error approach. However, due to cost and technical limitations, it is still hard to measure quality for every part. Removing data points of low-quality parts helps recommending proper process parameters. In this paper, we propose classification-based solution for recommending process parameters. In data preprocessing, the solution utilizes anomaly detection and knowledge-based methods to remove potential data points of low-quality parts without quality measures. On the processed data, a classification model is trained to predict process parameters according to blank properties. Our solution detects 30% low-quality parts and gives competitive performance (92.26% prediction accuracy) compared to a model trained on data comprising quality measures.

Keywords: classification; anomaly detection; process parameter recommendation

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1. Introduce

Stamping is commonly used in manufacturing of sheet metal parts for vehicle bodies because this process offers manufacturing advantages primarily in cost and time. In stamping operations, a sheet metal blank is fed into a stamping press and formed into a desired shape. However, geometrical precision of a formed part is affected mainly by the spring-back effect in the stamping process. After the tools are opened, the part changes its shape, which is called spring-back effect. As the contact forces between the part and the surface of the tool cannot act after opening the die, a new state of equilibrium is obtained, which is accompanied with the mentioned change of shape. The most influencing factors for the spring-back effect are tool geometry, process parameters, and blank properties, which comprises of elastoplastic and frictional properties [1]. Interaction between influencing factors determines the spring-back effect. Lim, Venugopal and Ulsoy demonstrate that an adaptive control of process parameters according to disturbances (e.g., lubrication and material property or thickness change) can reduce the spring-back effect in the stamping process [2]. Therefore, the recommendation of reasonable process parameters has caught growing attention from both academic and industrial experts. In the literature, there are abundant numerical studies on the selection of proper process parameters to achieve the expected part quality. A Finite Element (FE) model combined with an "inverse analysis" approach is developed to predict reliable spring-back effects with variant process parameters [3]. These studies give a good mathematical interpretation for the prediction with simplifications like assuming non-scattering blank properties and rigid tool surfaces. Owing to that simplifications of FE methods is seems to be difficult to predict a suitable choice of process parameters during production. For example, the effect of changing different cylinder forces on the quality of parts cannot be taken into account due to the assumption of rigid tool surfaces. Hence, in practice, the selection of process parameters is conducted based on an expert-driven trial-and-error method. At the beginning of an order for parts, an initial setting of process parameters, which is usually determined based on the knowledge and experience of specialists, is verified by manually inspecting the resulting quality. Usually, a search for proper process parameters required several try-outs until parts of accepted quality are produced. These try-outs result in significant downtime. Both FE and trial-and-error methods cannot work well when the blank properties vary at different locations of one blank or from blank to blank. With the advent of massive digitalization in industry, it is possible that plenty of data of material properties and machine configurations are gradually accumulated during production, which underpins a data-driven approach. A system is integrated in BMW press shops to obtain production data [4]. A regression solution is proposed, which determines the correlation between a set of process parameter combinations and their corresponding averaged blank properties and the solution is validated on the data points of good-quality parts [5]. A process parameter combination contains several different variables, for example cushion cylinder forces, configuration of spacer stroke rate, etc. But the number of actually used process parameter combinations is quite small compared to the total number of potential combinations because changes of process parameters are carefully made to ensure productivity and quality in manufacturing. In this paper, a classification-based recommendation of process parameters is proposed and validated on the data points of good-quality parts. We show in our work that a classification model achieves a good prediction accuracy and removing data points of low-quality parts identified based on quality data can improve the prediction performance. Nonetheless, due to cost and technical limitations, in general, quality data is less frequently gathered than process parameter data or blank property data for each part in manufacturing. A method to identify low-quality parts without quality data is valuable to be investigated in our research because the solution can be applied for parts whose quality is hard to be measured. Anomaly-detection and knowledge-based methods are introduced in our work to identify the low-quality part without using the quality data. It is prone that two methods can detect part of low-quality parts and removing detected data points can lead to train a competitive model compared to the model trained on only data points of good-quality parts. In summary, we demonstrate a classification-based solution for recommending parameters of production processes without using quality measures.

This paper is organized as follows. In Section 2, the concepts of classification, anomaly detection and performance metrics are briefly reviewed. Our developed solution is described in detail in Section 3, and in Section 4 the experimental results are presented. Finally, Section 5 concludes this article by discussing topics for further investigations.

2. Relative works

In this Section, we review related works. To the best of our knowledge, there is no similar work in the literature that uses a classification-based approach for process parameter recommendation. Therefore, we propose to give an overview of the ML methods applicable to this task, and to conduct an empirical comparison across those methods on our data set.

2.1. Classification

The classification problem is defined as the task to identify a category or class a new observation belongs to. A set of training data with known categories or class labels is used as the ground truth for learning a classifier (i.e., a trained machine learning model for classification). Based on the training data, a model learns patterns of categories. A candidate classification algorithm applied in our article for recommending configurations is the Random forest (RF) algorithm. A decision tree is a classifier that partitions the space recursively by considering one variable at each step and searching the optimal splitting threshold [6]. A random forest is an ensemble of decision trees that are constructed on independent bootstrap samples, which reduces the variance of decision trees and hence leverages the overall performance [7].

2.2. Anomaly detection

Anomaly detection is the task of detecting rare or unexpected data points, which deviate significantly from the majority of data points in a data set. In the following, several anomaly detection algorithms are introduced and used in our work:

- Histogram-based Outlier Score (HBOS) constructs a univariate histogram for each single feature, where the scaled height of each single bin estimates a density. HBOS of every data point p is computed by a multiplication of the inverse of the estimated densities corresponding to the data point's belonging bins. A data point with a high score shows a higher likelihood to be anomalous [8].
- One-class support vector machine (OCSVM) maps data points into a feature space via a feature map and separates them from the origin with maximum margin to capture most of the normal data points in a region [9].
- An Isolation Forest (iForest) uses a tree-structure to partition data points recursively until all data points are isolated from others. A data point that has a smaller depth in each decision tree indicates that this point requires a smaller number of partitions to be separated from the others and hence it is more anomalous [10].

2.3. Performance indicators

The models are evaluated by several metrics. In this article, the following metrics are based on four entries of the confusion matrix. The four entries are True Positive (TP), True Negative (TN), True Negative (TN) and False Negative (FN):

$$Accuaracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1\ score = 2 \cdot \frac{Precision \cdot Recall}{Precision+Recall} \tag{4}$$

The Kullback-Leibler divergence measures the proximity between two arbitrary probability distributions. In this article, we apply the KL-divergence on a predicted probability distribution and a reference probability distribution:

$$KL_{divergence} = q\ log\left(\frac{p}{q}\right) + (1-q)\ log\left(\frac{1-p}{1-q}\right) \tag{5}$$

Here, p is the predicted probability from a model and q, the reference probability derived from a testing data set, is 1 when a data point is of good quality, otherwise q is 0.

3. Our approach

3.1. Terminology

A data point represents a blank and contains data regarding its properties, applied process parameters, production conditions and quality measurements of the produced part. Good-quality parts are the parts, whose quality measurements satisfy all their acceptance criteria defined by specialists. In contrast, if one of part's quality measurements violates its criterion, the part is considered as low-quality. A raw data set is a collection of data points of both good-quality and low-quality parts. Detected data points are the data points, which are identified either by an anomaly-detection method or a knowledge-based method and removed from the training data set in the data preprocessing.

3.2. Our Solution

The solution consists of two parts, data preprocessing and modeling, as shown in Figure 1. In data preprocessing, two kind of methods are applied to detect data points representing low-quality parts. The first one is an anomaly-detection method applied on blank properties, and it detects blanks whose blank properties are significantly different from the majority of blanks. The second one is using knowledge-based methods (KBM) based on the attributes of production condition, for example, position in strips, stroke rates, and so on. The parts selected by KBM are considered to be produced in an unstable state of the process. All the data points detected by both of two methods are potential low-quality quality and will be removed from the training data set. In the modeling, the processed training data set is used to train a candidate model based on a RF algorithm.

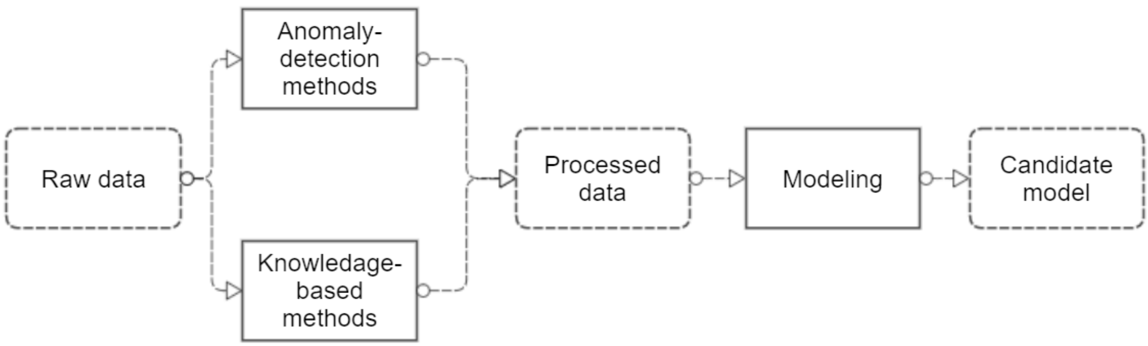

Fig. 1. Classification-based recommendation without quality measures.

The detection of potential low-quality parts is based on two assumptions about quality issues for the anomaly-detection and knowledge-based methods. The first one is that blanks with abnormal blank properties are likely to turn into parts with final quality problems, after completion of the forming step. This is due to the fact that a setting of process parameters is used which is suitable for the majority of the blanks. A blank with distinct blank properties demands an adjustment of the process parameters. However, for the sake of productivity in manufacturing, a change of process parameters causes downtime of a press line, which is inacceptable for a single blank. The other assumption is that production conditions could also affect the quality of parts. For example, the temperature of tools changes dramatically at the beginning of production because of the plastic deformation and friction and is relatively stable during production after a stationary state is reached. Material flow is sensitive to temperature, resulting in quality issues which are difficult to predict. The method for storing blanks can pollute the surface of blanks and redistribute lubrication. Consequently, we collected knowledge and experience from specialists in production and build up knowledge-based methods to detect the data points of low-quality parts. For example, we removed several data points, which are produced at the beginning of production or are located on the top of a blank stack.

3.3. Experimental design

An experiment is designed to validate our proposed solution in three steps, outlined in Figure 2. First, we show that a classification model is a good solution for the process parameter recommendation problem for the stamping process. A benchmark model of a RF algorithm is trained on a raw data set consisting of both good-quality and low-quality parts. Then, the performance of the model is evaluated on an independent testing data set comprising of only good-quality parts. Further, we prove that removing low-quality parts from the training data set can yield an improvement of the performance. A data preprocessing based on the quality measurements is conducted on the raw data set. The low-quality parts are identified by using the quality measurement and removed from the raw data set. A model trained on such a processed data without any low-quality part is compared to the benchmark model. Last, we show that anomaly-detection method and knowledge-based method can detect data points, which consist of most data points of low-quality parts and then using two methods in data preprocessing can yield a competitive model compared to a model with quality-measurement based data preprocessing. We apply anomaly-detection and knowledge-based methods on the raw training data set. All the detected data points are excluded from the training data set and remaining data points are used to train a candidate model. The performance of models is evaluated by three metrics, classification accuracy, weighted F1 score and KL-divergence and for the anomaly-detection method and the knowledge-based method, the metrics precision and recall are used in the next Section.

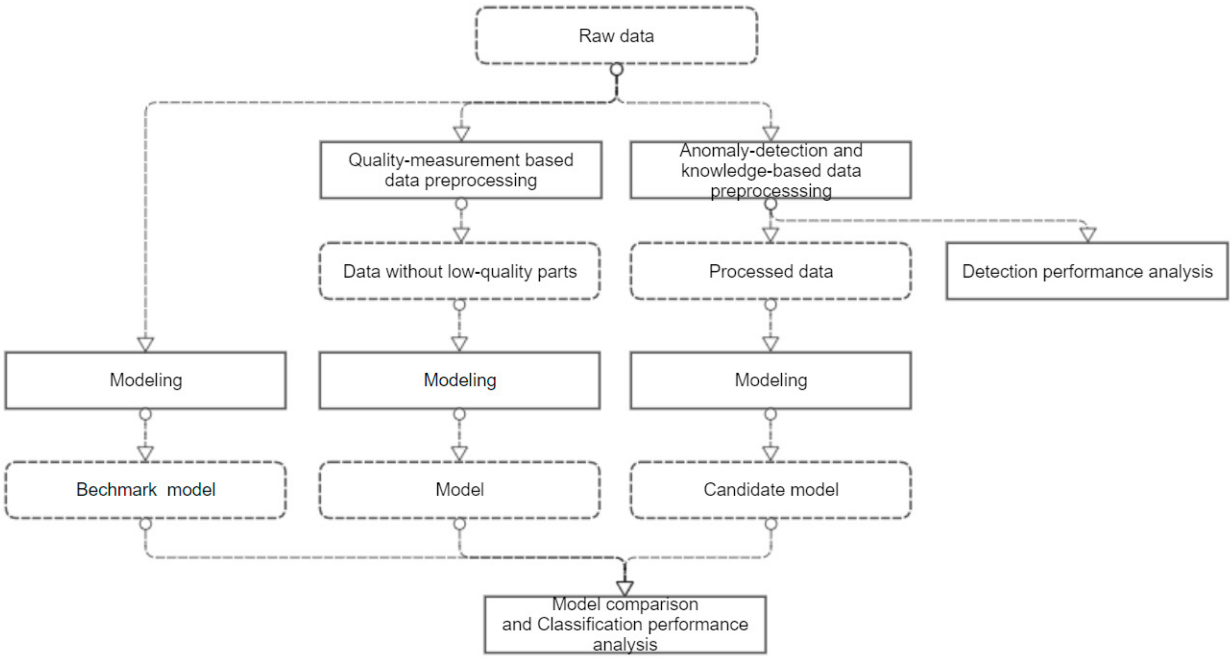

Fig. 2. Design of the practical experiment.

4. Experimental results

We evaluate the effectiveness of our solution on a real-world data set.

4.1. Data description

Our data refers to a roof, produced in a press shop of BMW, comprising 51570 data points. There are 57 attributes, including 43 attributes about blank properties, 6 attributes regarding production conditions, 8 attributes of process parameters and 9 quality measurements. In our investigation, the 8 process parameter attributes refer to forces of 8 cylinders of a drawing cushion and 43 attributes are the measurements of thickness and lubrication at different positions over a blank. 9 quality measurements are only used to distinguish the low-quality and high-quality parts and are not involved in training any classifiers. The blank properties and conditions are used in data preprocessing. The eight parameter attributes represent a total of 31 combinations of parameter settings that have actually been used in production for a period of 8 months. These are shown as classes with the corresponding frequencies in Figure 3. The whole data set is stratified split according to classes into a training data set (80%) and a testing data set (20%) to promise that all different classes exist in two data sets. The training and validation of models are conducted on the training data set and performance analysis is done on the testing data set.

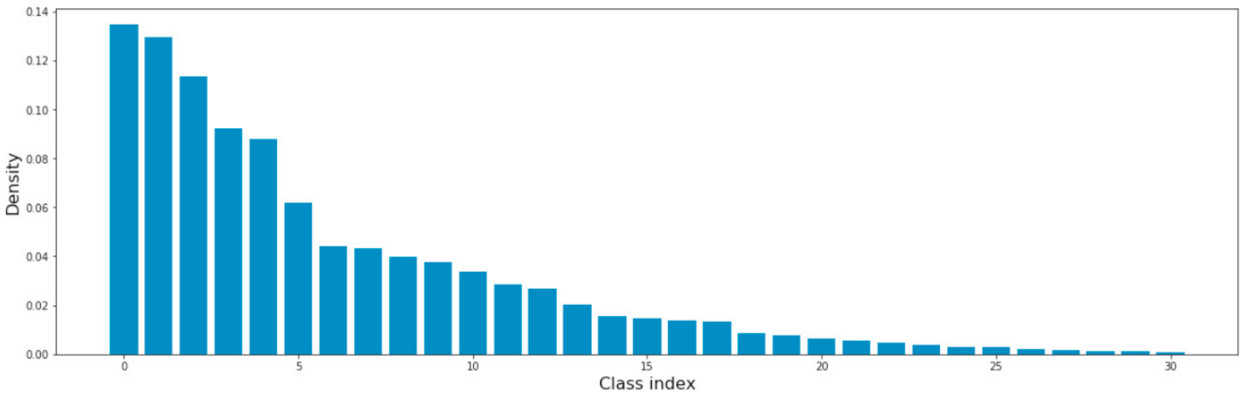

Fig. 3. Distribution of classes.

4.2. Detection performance analysis

To illustrate that anomaly-detection and knowledge-based methods can effectively detect data points of low-quality parts, an analysis of detection performance is conducted on the data set and performance is measured by the metrics recall and precision in Table 1. As all applied anomaly detection methods assign each data point an anomaly score, for a comparison, a 95% quantile value of all anomaly scores is selected to distinguish normal and anomalous data points. If the score of parts are larger than the 95%-quantile value, the data points are detected as anomalous. In this way, three different anomaly-detection methods have the same number of detected data points. The precision metric is an important performance indicator in our work and it shows the percentage of low-quality parts in the detected data points. As described in the Section 3.2, all detected data points will be removed from the training data set. A higher precision ensures that more data points of good-quality parts can remain in the training data set. According to the precision metric shown in Table 1, the OCSVM outperforms the other two anomaly-detection methods and is selected to be used in data preprocessing in our work. In addition, the anomaly-detection methods have a better precision performance than the knowledge-based method. We conclude that blanks with abnormal blank properties could cause more quality issues than production in an unstable process.

Table 1. Performance measurement.

Metrics	Anomaly-detection methods			KBM
	OCSVM	iForest	HBOS	KBM
Precision	42.63±0.31%	41.61±1.16%	40.67±0.21%	15.39%
Recall	22.51±0.16%	21.86±0.61%	21.37±0.11%	11.29%

The recall metric demonstrates that the OCSVM method found 22.51% of all low-quality parts and the knowledge-based method detects 11.29%. The further investigation of detected data points in Table 2 shows that only 1.57% of low-quality parts are detected by OCSVM and KBM at the same time, because the anomaly-detection methods and the knowledge-based method detect low-quality parts based on different assumptions about quality issues. A small intersection of detected low-quality parts between two methods confirms the mutually independent two assumptions about quality issues. The knowledge-based method detects around 9.73% low-quality parts, which are considered as high-quality by anomaly-detection methods, in contrast, the anomaly-detection method found about 19.93% to 21.05%. We conclude that it is worthy to use two different methods at the same time to detect low-quality parts.

In the next Subsection, we show that, although two methods detect partial low-quality parts and drop several data points of good-quality parts as well, removal of partial low-quality parts can effectively improve the classification-based models for process parameter recommendation.

Table 2. Methods comparison on detected data points (Low: Low-quality parts, Good: Good-quality parts).

	OCSVM-Low	OCSVM-Good	iForest-Low	iForest-Good	HBOS-Low	HBOS-Good
KBM-Low	1.57%	9.72%	1.65%	9.64%	1.45%	9.84%
KBM-Good	21.05%	67.89%	20.21%	68.50%	19.93%	68.78%

4.3. Model hyperparameter selection

For each model, a hyperparameter selection is conducted on stratified 5 folds of its own training, for example, the processed data for the candidate model, shown in the Figure 2.0. The hyperparameter setting of the Random Forest, a number of estimators 140, a depth 13 and a criteria entropy, yields the best performed setting.

4.4. Classification performance analysis

Table 3 summarizes the performance of the benchmark model, the candidate models (iForest+KBM, OCSVM+KBM, HBOS+KBM) used in our approach, and a model with quality-measurement based data preprocessing (called “Model” in the table). According to the performance of the benchmark model, the RF algorithm performs the recommendation task well, obtaining at least 88.19% accuracy. In addition, there are multiple classes in the problem, and the RF algorithm yields a good result indicated by the weighted F1 score, which considers the number of correctly predicted data points for each class and takes class imbalance into account.

The performance comparison between the benchmark model and the model with quality-measurement based data preprocessing (“Model”) provides evidence that removing data points of low-quality parts helps in classification tasks and improves accuracy and F1 scores from 88.19% and 87.50% to a maximum of 92.26% and 91.83%, respectively. For a low-quality part, it is supposed to be rescued by adapted process parameters. However, the proper process parameters for low-quality parts are unknown to us. Also, a correct prediction for a low-quality part makes no sense when measuring the performance of models. But it is still expected to gain information about prediction of low-quality parts. Thus, KL-divergence is used to leverage data points of low-quality parts. KL-divergence measures the deviation between a predicted distribution of a model and an approximated distribution. RF not only gives a predicted class to a data point but also estimates possibilities of each class for the data point. We set up an approximated possibility as 1 for the class of a data point of good-quality part. In contrast, for a low-quality part, its class should be close to a possibility of 0. Because we can confirm that its own class in the data set are supposed to be avoided and obtain a low predicted possibility, even though a proper class for it is unknown. According to KL-divergence, low-quality part removal helps reducing 34.65% of KL-divergence compared to the benchmark model and penalizes predicted possibilities of labeled classes of data points of low-quality parts as well as increases possibility for data points of good-quality parts.

Based on the performance of candidate models, the candidate model of One-class Support Vector Machine and knowledge-based method achieves a competitive performance compared to the model with quality-measurement based data preprocessing. The model of OCSVM and KBM outperforms the other two candidate models and has a 92.47% prediction accuracy and 91.83% weighted F1 score. On these two metrics, the candidate model of OCSVM and KBM shows similar performance to the model with quality-measurement-based data preprocessing. The KL-divergence shows that a quality-measurement based data preprocessing decreases KL-divergence of the benchmark model from 0.7138 to 0.4694, i.e., by about 34.65%. The candidate model of OCSVM and KBM reduces KL-divergence from 0.7138 to 0.5690, i.e., by about 20.28%, with removing 32.23% data points of low-quality parts. The removal of partial low-quality parts can already significantly improve performance of the classification-based model

Table 3. Classification result on the real-world data set.

	Model	OCSVM-KBM	iForest+KBM	HBOS+KBM	Benchmark
Accuracy	93.06%	92.47%	92.11%	92.26%	88.19%
Weighted F1 score	92.52%	91.83%	91.46%	91.55%	87.50%
KL-divergence	0.4694	0.5690	0.5766	0.5694	0.7138

5. Conclusion

Based on results on a real-world data set, we reach several conclusions. First, a classification-based solution can perform well for the recommendation task. Then, the low-quality part removal helps improving the performance of process parameter recommendation. Further, using anomaly-based detection and knowledge-based methods to detect and remove partial low-quality parts instead of the quality-measurement based method can yield a well-performing recommendation. Our solution can be generally used for other parts without quality measurements. The further investigation is to apply and validate the solution in the real production setting. Although, two kinds of methods detect maximally 32.23% of low-quality parts, it is possible to find others, when the other influencing factors are introduced, for examples, roughness, material strains, temperature of tools und etc.

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