Materials Research Proceedings **25** (2023) 323-328 https://doi.org/10.21741/9781644902417-40

# Definition and validation of a customized classification system for sheet metal bending parts

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**Keywords:** Optimization, Bending, Sheet Metal

**Abstract.** The industry demands an increasing individualization, which leads to a rising variety of sheet metal parts. The consequence for sheet metal manufacturers are larger amounts of product data, smaller batch sizes and a larger quantity of different parts per year. The challenge for an efficient company is the availability and use of the corporate product data. Classification is a suitable tool for organizing corporate product data sets. In order to better reflect the individualization of customer demands and the resulting flexible manufacturing processes in a classification system, a method is needed to adapt the classification system based on the frequently used feature list. In the context of this paper, features are defined and parts are classified that are manufactured with the technology of air bending. It is a contribution to the creation of more precise approaches to the sheet metal part classification with simultaneous validation by a measurable characteristic. Focus is placed on the validation of the system with empirical measurement data. This allows every company to optimize and validate their own classification system.

## Introduction

Over the last decades, the increasing individualization of customer demands led to a rising variety of sheet metal parts [1]. The result is a wide spectrum of sheet metal products, that ranges from simple articles of daily use to precision parts for the automotive or aviation industry [2]. Especially the aviation industry today is largely based on sheet metal forming technologies [3]. Due to individualization, product data is growing in all departments of a company like development, industrial engineering or production, as new products are constantly being developed or old products are being modified [4]. Manufacturers of sheet metal parts have adapted to the new situation. Associated with the larger variety of sheet metal parts, a significant range of flexible manufacturing processes for the production of those were developed [2]. The direct consequence for sheet metal manufacturers are smaller batch sizes and a larger quantity of different parts per year [5]. In addition, they have to handle larger amounts of product data for the higher variety of different parts.

In this environment it is important to find an efficient way to cope with the amount of data. The challenge for an efficient company is the availability and use of the corporate product data [6]. Classification is a suitable tool for organizing corporate product data sets and thus allows access to empirical knowledge [4]. Greska recognized that classification is a basic strategy for acquisition and processing of knowledge [6]. The necessity of a classification system becomes obvious when engineers of a manufacturing company spend on average about 45 % of their working time to search for existing parts and assemblies [6]. A review from Duflou et al. [7] has shown that a large number of publications contain proposed classification systems, that differentiate between certain features of design or manufacturing. Gupta et al. [8] use also features as they distinguish between deformation and cut features. In their work, they define sheet-metal parts as a combination of a number of individual features and each feature is related to another directly or indirectly. Furthermore, Greska et al. [6] give an overview of the three types of classification systems: 1. form order systems, 2. special feature list and 3. pattern recognition. The form order systems are almost irrelevant, as they are error-prone and time-consuming. An example of a frequently used feature list is a classification code. That code can be derived in form of a five-sign chain, based on the analysis of different features of parts [9]. The research is focused on automated processes and artificial intelligence methods to recognize patterns and features of parts and classify the parts into categories [7]. The methods cover a wide range of manufacturing processes [4]. The automated approach has yet been only partially successfully applied in most industrial companies.

To better reflect the individualization of customer demands and the flexible manufacturing processes, a method is needed to adapt the frequently used feature list. A classification system tailored to the specific manufacturing process of a company contributes to increasing this rationalization potential [10]. To achieve the target of an appropriate classification system, a process is required that adapts the classification system to the manufacturing process. The selected classification system must be validated against measurable data. A specific classification system supporting the different work processes could be created for each functional department of a company, e.g., purchasing, customer service, sales, or engineering [4]. This paper is a contribution to the creation of a more precise approach to the sheet metal part classification with simultaneous validation by a measurable characteristic. To overcome some limitations of general classification system, a method is shown for developing a classification system that fits the process.

## Experimental Procedure

Feature list and calculation of the complexity score. In the context of this paper, parts are classified that are manufactured with the technology of air bending. The achievable dimensional accuracy in air bending is dependent on variations in sheet thickness and material properties, because these lead to variations in springback [2].

The production of tightly toleranced bending angles therefore requires a good execution of the process [2]. The major advantage of air bending over the other frequently used technology die bending is its much greater flexibility, because one tool can be used for many bending angles and radii [11]. In order to determine the relevant features for a feature list of the air bending process, the basic studies of Greska et al. [10] are used. With this set of features as a basis, the features fitting to the air bending process are selected. Additional features are combined with them based on expert knowledge from engineering and production. The initial selection includes 28 features, which are shown in Fig. 1. To facilitate data analysis and to be able to compare and rank parts, a complexity score (CS) is introduced. Once the complexity of parts can be quantified, re-use of the knowledge available for certain categories of parts is possible [7]. The CS is generated out of the selected features. To quantify the complexity of the parts, the weighting of the features is necessary using the method of pairwise comparison. In addition, a normalization of the feature values is done to the range 0 to 10. As a result the different feature values become comparable and the differentiation of the final CS score is improved. The CS is the sum of the normalized feature values multiplied by the weighting. The theoretical maximum range of the complexity score is up to 1000. The actual parts assessed are in the range from 51 to 468.

Validation of the features based on the measurement results. In order to validate the classification system for the air bending technology, a hypothesis is formulated which is verified using actual measurement data. The hypothesis is the higher the complexity score of the part, the larger is the deviation of the profile shape tolerance. To verify the hypothesis a selection of sample parts from the company’s portfolio needs to be defined with a minimum of three parts per set. For this paper, sample parts of RECARO Aircraft Seating GmbH & Co. KG are used to demonstrate the method for the air bending technology. The selection is made on the basis of the geometry and the production quantity with an amount of selected parts less than 15 to be cost effective. The selection of parts is optimized according to the most possible appearance variety and the largest production quantity. The selected parts are classified on basis of the developed complexity score, manufactured with a batch size of 20 and measured for an empirical data set. The measurement data are used to investigate the correlation of complexity score and the deviations of the parts based on the profile shape tolerance. The average values of the profile shape tolerances of a production lot are determined. The correlation between averaged profile shape tolerances and complexity score is calculated. Additionally, a scatterplot is created for the visual interpretation of the empirical data. Recognizing an association in the pattern does not guarantee that there is actually a cause-and-effect relationship between the variables [12]. The calculated correlation coefficient is a measure of the strength of the relationship between the two variables and does not imply causation. Based on this, it is important to conduct a substantive interpretation of the correlative relationship to justify causality.

| | |
|---|---|
| **Flat pattern** – geometry and further features | material properties<br>length [mm]<br>width [mm]<br>thickness [mm]<br>symmetrie of outer contour [yes/no]<br>symmetrie of inner contour [yes/no]<br>boreholes/sinkholes in critical area [yes/no]<br>number of bend lines [qty.] |
| **Flat pattern -** orientation of the bend lines | number of bend lines parallel to the length of the part [qty.]<br>number of bend lines at 90° to the length of the part [qty.]<br>number of bend lines at a "free" angle [qty.] |
| **Finished part -** dimensions | length [mm]<br>width [mm]<br>height [mm]<br>price per part [€] |
| **Finished part -** geometry | number of bending segments [qty.]<br>max. length of beding segment [mm]<br>related height of segment[mm]<br>related angle [deg]<br>related radius [mm]<br>number of L/90°-bends [qty.]<br>number of U-bends [qty.]<br>number of Z-bends [qty.]<br>number of double-Z-bends [qty.]<br>number of free angle [qty.]<br>number of boxes [qty.]<br>number of layers [qty.]<br>appearance [closed / open] |

*Figure 1: Feature list for air bending*

Reduction of features and verification of correlation. For an efficient classification system, it is evaluated whether the initial number of features can be reduced. To evaluate the reduction of the features, a linear optimization is performed based on the sample parts. Using linear optimization, the weighting factors of the score are modified to improve the correlation between averaged profile shape tolerances and the part's complexity score. With this approach, non-relevant features can be excluded from the calculation of the score. Further parts from the company's portfolio are added in order to verify the linear optimization performed. In most companies, measurement data from first article reports (FAI) of parts are available. All measurement data used in this paper are measured with the scanner system ATOS Compact Scan. The measurement data of these parts are used to check the correlation between complexity score and the profile shape tolerance.

## Results and Discussion

The scatterplot in Fig. 2 shows the distribution of the parts based on the profile shape tolerance in relation to the complexity score. The position of the dots indicates values for an individual data point of the sample. The 62 blue dots represent parts with one measured value, during the part first article inspection. The eleven orange dots are average values (n = 20) of the profile shape tolerances of the selected sample parts. The sample correlation coefficient (r) shows a strong positive association between the computed complexity score and the measured profile shape

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tolerance. When looking at all the 73 parts, the correlation coefficient r is 0.75. Limiting the correlation coefficient to the 11 parts used to optimize the system with the linear optimization, the value increases to 0.93, which means a very strong positive association.

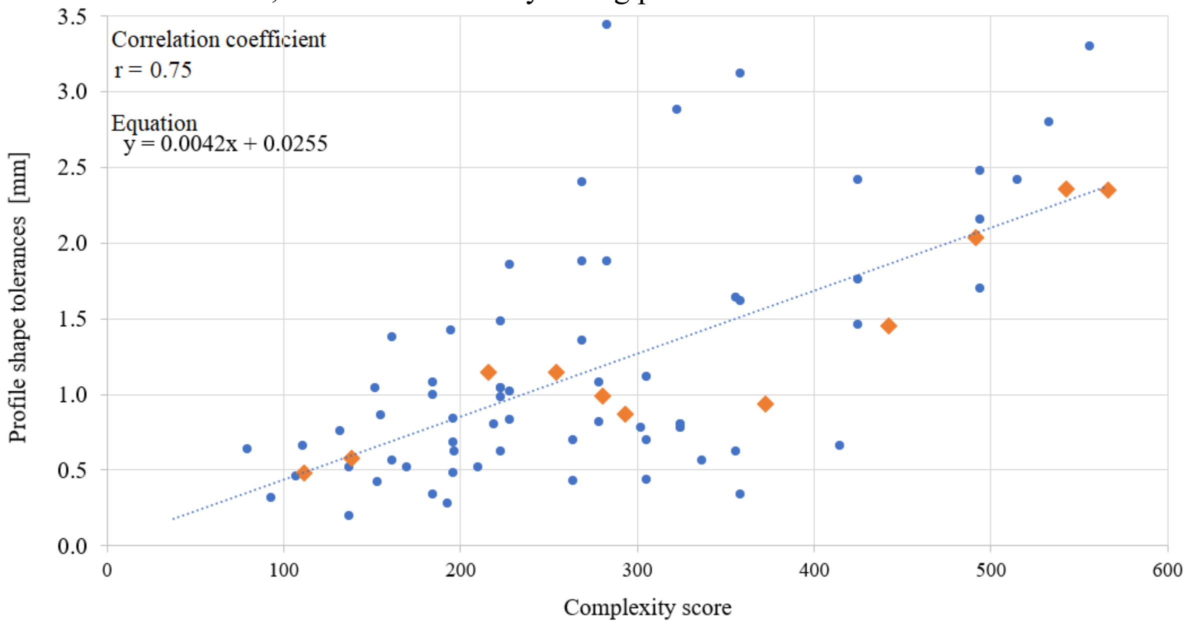


*Figure 2: Correlation between complexity score and profile shape tolerances; orange: measurement series, averaged n = 20, blue: single parts n = 1*

The hypothesis is the higher the complexity score of the part, the larger is the deviation of the profile shape tolerance. The association between the two variables is strong, therefore the hypothesis is verified. However, evidence of a correlative association does not guarantee that there is causation [12]. Interpreting the causal relationship, the feature list from Fig. 3 is taken into account. A causal relationship exists if the remaining features have an impact on the profile tolerance. The initially selected classification features are reduced using the linear optimization from 28 to 11. Only features of the finished part are used to compute the optimized complexity score. Features such as dimensions of the finished part or the number of determined bending lines, e.g., the number of U-bends, are also confirmed in the literature as influencing variables for part accuracy. Greska et al. [6] show the factors impacting the part accuracy and Söderberg et al. [13] describe the different geometrical sensitivities that lead to variation in individual part dimensions. The individual part dimensions are reflected in the profile shape tolerance as it is defined as a 3-D tolerance zone around a surface. Therefore, the relationship between CS and profile shape tolerance is considered causal. With the validation, the classification system is ready to use in all relevant departments of a company. Furthermore, a process is defined based on the data and experience gathered during the experiment.

The developed process works for all sheet metal bending technologies and is a more precise approach to the sheet metal part classification due to the simultaneous validation by a measurable characteristic. It overcomes the limitations of general classification system, by using features for classification which fits the specific process. Fig. 4 visualizes the process and describes the four steps to a customized classification system. It uses the available knowledge from literature and experts to derive features.

| | |
|---|---|
| **Flat pattern –** geometry and further features | 0% material<br>0% length [mm]<br>0% width [mm]<br>0% thickness [mm]<br>0% symmetrie of outer contour [yes/no]<br>0% symmetrie of inner contour [yes/no]<br>0% boreholes/sinkholes in critical area [yes/no]<br>0% number of bend lines [qty.] |
| **Flat pattern -** orientation of the bend lines | 0% number of bend lines parallel to the length of the part [qty.]<br>0% number of bend at 90° to the length of the part [qty.]<br>0% number of bend at a "free" angle [qty.] |
| **Finished part -** dimensions | 20% length [mm]<br>10% width [mm]<br>40% height [mm]<br>0% price per part [€] |
| **Finished part -** geometry | 50% number of bending segments [qty.]<br>20% max. length of beding segment [mm]<br>0% related height of segment[mm]<br>0% related angle [deg]<br>0% related radius [mm]<br>10% number of L/90°-bends [qty.]<br>10% number of U-bends [qty.]<br>10% number of Z-bends [qty.]<br>10% number of double-Z-bends [qty.]<br>10% number of free angle [qty.]<br>10% number of boxes [qty.]<br>0% number of layers [qty.]<br>0% appearance [closed / open] |

*Figure 3: Reduced feature list for air bending after linear optimization*

Room for improvement lies in the area of digitalization and Industry 4.0. One challenge is to automatically collect the features in an end-to-end PLM system. This increases efficiency and contributes to a company-wide use of the classification system. After the developed classification system has been validated by empirical measurement values, it is still required to define what actions are required in the individual departments depending on the score. For example, at high values of the CS, a simulation of the part or the production and measurement may be necessary.

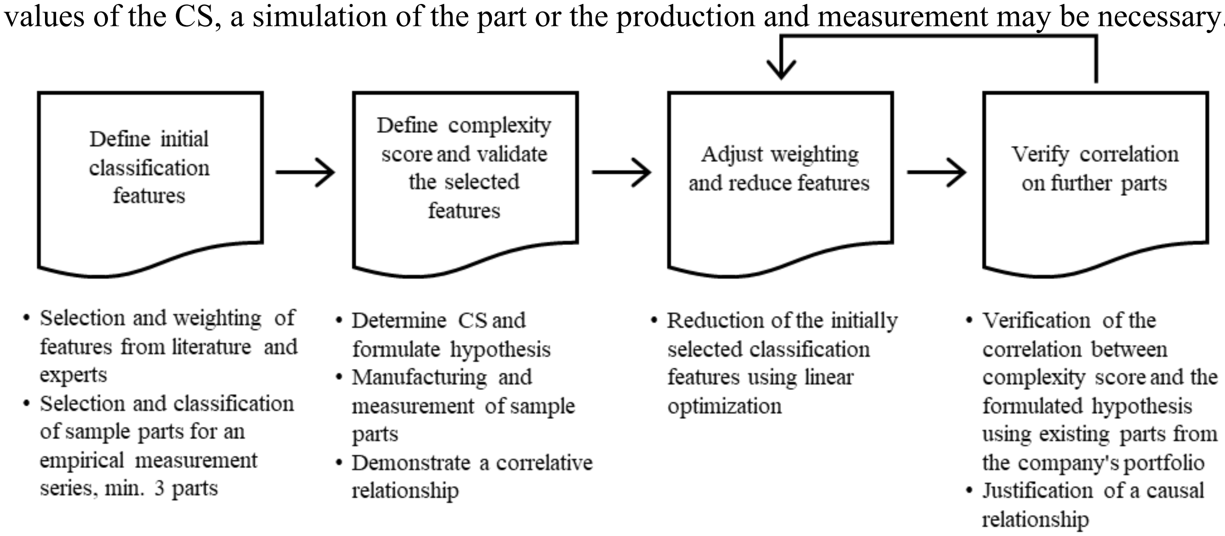


*Figure 4: Technology-based approach to a customized sheet metal part classification*

## Summary

Within this paper a technology-based approach to a customized sheet metal part classification system is introduced. The individualization of customer demands and the flexible manufacturing processes require a precise classification. The customized classification system eliminates the restrictions of a general classification system. Because of the success in the industry, a feature-based classification is customized to one specific manufacturing process. A method is shown for developing a classification system that fits the process. The relevant features for the air bending technology are identified and weighted. A complexity score is computed based on the selected features. To quantify the complexity of the parts, weighting of the features is necessary using the method pairwise comparison. In addition a normalization of the feature values is done to the range 0 to 10. The complexity score is the sum of the normalized feature values multiplied by the weighting. The hypothesis defined at the beginning of the experiment is verified, which means that the developed classification system is relevant for the considered air bending technology. The sample correlation coefficient (r = 0.75) shows a strong positive association between the computed complexity score and the measured profile shape tolerance.

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