Machine Learning for the Prediction of Brake Bending Parameters

some hyped-up tagline

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Abstract

This is the abstract. Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

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Introduction

Sheet metal forming has been used for centuries in different manufacturing industries to create a wide range of products for different applications. Sheet metal bending and stamping can be considered as the most important variants in the forming industry. (Cruz et al., 2021, p. 1) Therefore these have been continuously improved in recent decades to meet the growing demand especially in automotive and aircraft industries with the goal to reduce energy efficiency and emissions. (Zheng et al., p. 4)

Sprinback is a common phenomenon in sheet metal forming processes. It is a deformation of the sheet metal that occurs when the sheet metal is bent. Therefore, predicting the spring back is important to reduce the number of trial and error cycles in the manufacturing process. (Cruz et al., 2021, p. 1) Sheet metal forming is a complex process that involves a large number of variables and parameters Therefore, it is difficult to predict the spring back accurately, which makes it an interesting case for machine learning.

In order to predict springback with minimium errors, this thesis build and evaluates different machine learning models to predict the springback of a sheet metal. The models are evaluated based on the mean absolute error (MAE) and the root mean squared error (RMSE). The best model is then used to predict the springback of a sheet metal with different parameters.

1.1 | Problem statement

With the rapid development in manufacturing and increasing demand for high-quality products, the requirement to produce parts with high precision and accuracy has become a need of the manufacturing world, since it is known that springback is an undesired outcome, so the need for minimizing this in sheet metal parts is of utmost importance, this could not be achieved by adopting traditional approaches to predicting springback, so a newer approach known as a machine learning approach is adopted. Machine learning is a branch of Artificial intelligence in which, given input data points and output value, a computer algorithm learns rules by Analyzing the data. In other words, it gives systems the ability to learn and improve themselves without explicitly being programmed. The recent advancement in technology and the development of manufacturing 4.0 also triggered the need for machine learning. It means that the machines are producing data at an unprecedented scale, so now it is needed to have fast learning algorithms that can give accurate results in a short amount of time. (Baig et al., 2021)

2

Theoretical Foundations

2.1 | Sheet Metal Bending

2.1.0.1 | Sheet Metal

Sheet metal is any form of that has a relatively large length to thickness ratio, their thicknesses are typically from 0.4mm to 6mm. (Baig et al., 2021) Parts made of sheet metals are manufactured with different methods, such as stamping, bending, shaping etc. Bending is one of the most common methods to manufacture sheet metal parts.

2.1.0.2 | Bending

Bending is a forming operation that is used to change the shape of a sheet metal. The applied load is beyond its yield strength but below its ultimate tensile strength to achieve a permanent deformation (Baig et al., 2021, p. 1) During bending the metal on the outside of the neural plane is stretched and the metal on the inside of the neutral plane is compressed. The neutral plane is the plane that is perpendicular to the bending axis. (Baig et al., 2021, p. 3)

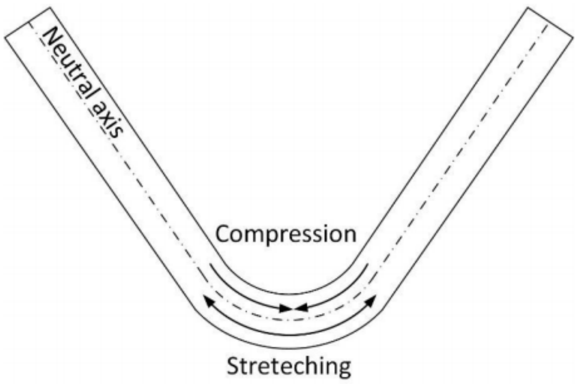

Figure 2.1: Bending plane, compression and stretching of sheet metal (Baig et al., 2021, p. 3)

2.1.0.3 | Air Bending

To bend sheet metal different methods like air bending, coining and brake bending can be used. A very common bending method is V-Bending, where bending operation are performed using punch-and-die tooling. One operation which can be performed in V-Bending is air bending. (Groover, p. 416) In this process the punch sheet metal comes in contact of the outside edges of the die, as well as the punch tip but it does not come in contact with the die surface. It is typically the preffered bending method because its high flexibility because it is possible to achieve different bending angles using the same punch-and-die tooling. (Cruz et al., 2021, p. 1)

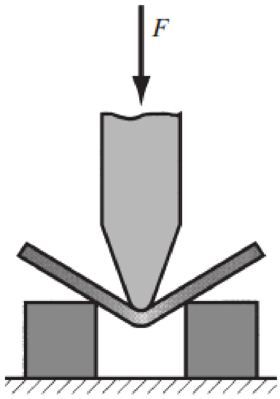

Figure 2.2: Air bending (Groover, p. 416)

"However, this process is characterized by strong nonlinear behavior, considering its parameters and their interrelationships [3]." (Cruz et al., 2021, p. 1)

2.1.0.4 | Spring Back

When the punch and therefore the bending pressure is removed at the end of the deformation operation, elastic energy remains in the bent part. This elastic energy is released and the metal sheet partially returns to its original shape. (Groover, p. 113-114)

To address this issue there are several methods to compensate the spring back. For example one common method is over bending, which means that the punch angle and radius are fabricated smaller than the specified angle. (Groover, p. 114) Prerequisite for all compensation methods is that the springback is known therefore the accurate prediction of the springback play an important role in the manufacturing process.

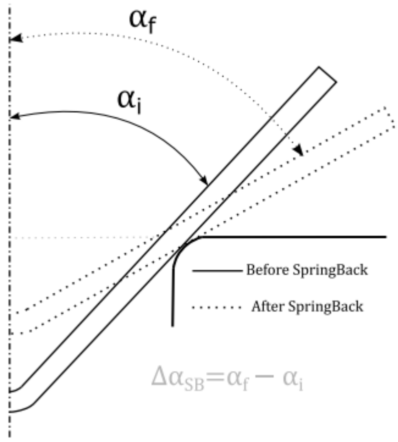

Figure 2.3: Spring back (Cruz et al., 2021, p.)

2.2 | State of research

With the availability of data there has been an increased use of Machine Learning Machine Learning (ML) in sheet metal forming with the goal to reduce costs and increase manufacturing quality. Bock et al. (Cao et al.) The ML algorithms can be divided into the main categories supervised learning, unsupervised learning and reinforcement learning. (Liu et al., a) Supervised learning is generally used in classification problems and regression problems while unsupervised learning is used to find patterns in data (Cruz et al., 2021, p. 2).

Spring Back Prediction Using Unsupervised Learning

Artificial Neural Networks Artificial Neural Network (ANN)s are widely used in sheet metal forming because of their high accuracy and generalization performance. (Cruz et al., 2021, p. 2) (Narayanasamy and Padmanabhan) which compared regression and neural network modeling for predicting spring back of steel sheet metal during the air bending process. They observed that ANN was able to predict the spring back with higher accuracy. But they had a sample size of 25 and suggested further research. (Inamdar et al.) developed an ANN for the air bending process to predict spring back as well as the punch travel to achieve the desired angle in a single stroke. (Kazan et al.) developed an ANN trained with FEM simulation data to predict the spring back for the wipe-bending process.

Because ANNs need a large amount of data to train the model generating the data with real machines is a time-consuming process. Therefore, it is common to use ANNs trained with Finite Element Method Finite Element Method (FEM) simulation data. *Was sind die Nachteile von FEM? Warum nutze eich "echte" Experimente?*

Spring Back Prediction Using Supervised Learning

Liu et al. (2019) used a Support Vector Machine Support Vector Machine (SVM) to predict the spring back of micro W-Bending operations. Liu et al. (b) Dib et al. (2019) compared different ML techniques (logistic regression, SVM, KNN, ANN, random forest, decision tree, naive Bayes, MSP) to predict the spring back and the occurrence of defects in sheet metal. (Dib et al., p. 1) The authors conclude that the MLP and the SVM are the best performing algorithms and suggest further studies of ML regressions models and kriging regression models. (Dib et al., p. 13)

3

Research methodology

The research method used in this thesis follows the design science research (DSR) approach (von Rennenkampff et al., 2015, p. 17). DSR is a research paradigm in which the designer tries to create artifacts to answer questions for problems.

DSR is a research paradigm in which the designer creates artifacts and uses them to answer questions for problems and generate new scientific knowledge. The designed artifacts are both useful and fundamental to understanding the problem (Hevner and Chatterjee, 2010, p. 10)

Design, according to Peffers et al. (2007), is the creation of an applicable solution to a problem (Peffers et al., 2007, p.47)

According to Hevner et al. (2010) design" is both a process ("a set of activities") and a product ("artifactt"). (Hevner and Chatterjee, 2010, p.78) The design-oriented research approach as a methodological framework seems well suited to answer the research questions. Predicting spring back and bend deduction is a relevant problem in business practice. Also, the conception and implementation of machine learning models is a design activity.

The term artifacts is intentionally broad and can take on different forms. In this work, the artifact is different machine leaning models which are applied on the generated data. DSR can be implemented in various ways, a prominent example is provided by Peffers et al. and shown in Figure 3.1 The approach comprises six steps, which are dived into the superordinate phases "Build" and "Evaluate". This thesis follows these phases.

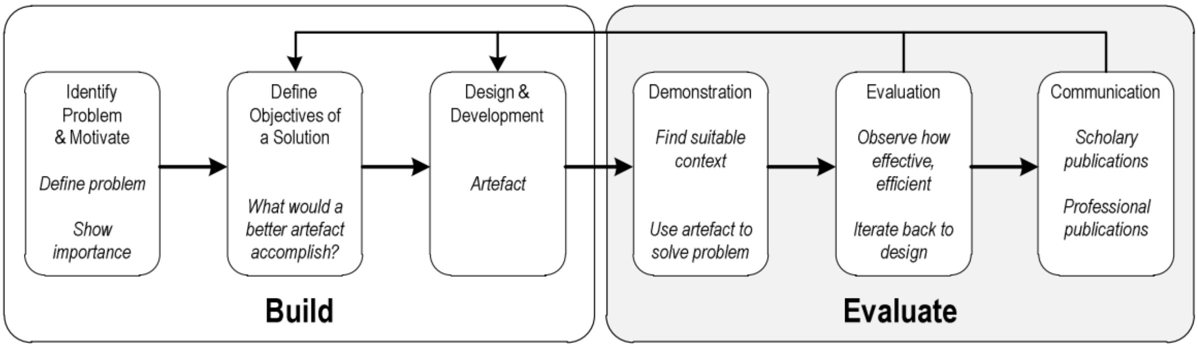

Figure 3.1: Design Science Research Approach according to Peffers et al.
Picture: (Sonnenberg and vom Brocke, 2012, p. 72)

Activity 1 - Problem identification and motivation This activity includes defining a specific research problem and the value of a potential solution. The problem is used for the development of the artifact. To reduce complexity, the problem should be divided into sub-problems. For problem-solving, explicit methods such as system requirements gathering or an implicit method such as programming and/or data analysis. (Peffers et al., 2007, p. 52)

Activity 2: Define the objectives for a solution The goals of a solution are derived from the problem definition. These are derived in the context of what is possible and feasible. Objectives can be quantitative or qualitative. Objectives should be derived from the problem specification and are thus based on the previous step. For knowledge about previous solutions and their effectiveness are required (Peffers et al., 2007, p. 55)

Activity 3: Design and development This step involves the creation of the artifact. An artifact can potentially contain models, methods or constructs, it can be anything that contributes to the solution of the research question. This step includes the definition of the functionality and architecture of the artifacts, followed by the creation of them. (Peffers et al., 2007, p. 55)

Activity 4: Demonstration The use of the previously created artifactt is demonstrated for one or more problems. This requires effective knowledge of the artifact. (Peffers et al., 2007, p. 55)

Activity 5 - Evaluation It is observed and evaluated how well the developed artifact provides a solution to the defined problems in activity 1. Knowledge of relevant metrics and methods of analysis is assumed. Depending on the nature of the problem, the evaluation can take different forms. A comparison of the functionality of the artifact and other solutions can be considered. Furthermore, quantified quantified parameters can be used to measure the performance of the artifacts (Peffers et al., 2007, p. 56) Hevner et al. suggest five different evaluation methods: Observational methods, analytical methods, experiments, testing of the artifact and descriptive methods (Hevner et al., 2004, p. 87)

Activity 6 - Communication The problem and the artifactt and its benefit are communicated externally (Peffers et al., 2007, p. 56) Hevner et al. describe in a conceptual framework guidelines for the

3.1 | Design Principles

Design Principles (DP) are seen as a central part of design-oriented research. (Gregor et al., 2013, p. 348) Design principles are characterized as "principles of form and function" as well as "principles of implementation" of an artifact. (Gregor and Jones, 2017, p.8) They are used to close the gap between researchers and user and allow prescriptive research on systems. They are used to capture knowledge about the artifact. (Sein et al., 2011, pp. 37-56). Koppenhagen et al. suggest generating design principles by grouping requirements for the solution and then creating core requirements, which can which can then be DPs. (Koppenhagen et al., 2012, p. 6)

3.2 | Evaluation of Machine Learning Models

In the field of software engineering there are already standards that define the quality of software systems and its components like ISO/IEC 25010. (Siebert) noted, that such standards can not applied directly to ML and therefore need to be adapted. Therefore they re-interpreted and extended these existing quality models to the ML context. (Siebert, p. 1) In order to define the Design Principles for the artifacts in this work, the considerations of (Siebert) are used. This enables a systematic process in order to assess the quality of the developed artifacts.

3.2.1 | Goal Question Metric Approach

To make the defined quality attributes measurable, the “Goal-Question-Metric”-approach GQM was chosen in this work. It is one of the most common approaches in DSR and is divided into three levels. (Basili et al., 2002, p. 3)

1. Conceptual level (goal): "A goal is defined for an object, for a variety of reasons, with respect to various models of quality, from various points of view, relative to a particular environment." (Basili et al., 2002, p. 3)

2. operational level (question): "A set of questions is used to characterize the way the assessment/achievement of a specific goal is going to be performed based on some characterizing model. Questions try to characterize the object of measurement (product, process, resource) with respect to a selected quality issue and to determine its quality from the selected viewpoint." (Basili et al., 2002, p. 3)

3. quantitative level (metric): "A set of data is associated with every question in order to answer it in a quantitative way." (Basili et al., 2002, p. 3)

Objectives, questions and metrics can be presented in a hierarchical structure.

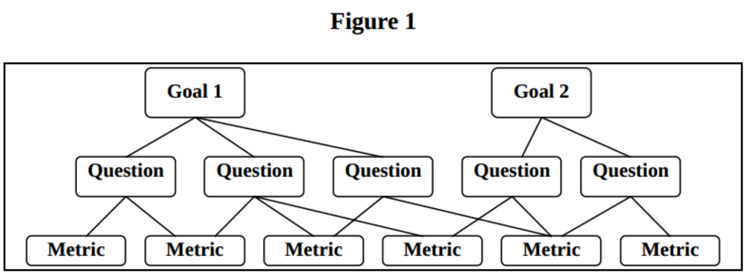

Figure 3.2: Goal-Question-Metric Ansatz (Basili et al., 2002, p. 3)

4

Build

4.1 | Dataset generation

For the dataset generation, bending experiments were performed on metal sheets with different thicknesses. The material used is cold rolled steel sheets of the norm DIN EN 10130. The thicknesses used were 0.5mm, 1mmm and 2mm. The material was used because it is commonly used in bending processes and its high availability. In previous tests, it was observed, that the spring back are well observable with this material. Using this material, 200 single bending pieces of the dimension 20×100 mm have been cut. Each piece was bend one time using a *Zwick* three-point-bending machine.

Python script where developed to covert the output data format from the machine to CSV files. The following describes the experimental setup used for the experiments performed.

4.1.1 | Experimental setup

The setup consists of a three-point-bending machine with a punch and a die with no bottom. The machine used is the *Zwick MX 25A* material testing machine. The machine is equipped with a load cell and a displacement sensor. The load cell is used to measure the force applied to the sheet and the displacement sensor is used to measure the displacement of the punch. The machine is controlled by a computer and a software called *ZwickRoell TestXpert*. The software is used to control the machine and to save the output data.

The experimental setup and its parameters are shown in Figure 4.1 where V is the die opening, y_p is the punch penetration which is the distance the punch is moved into the sheet. The paramter t is the sheet thickness, α is the sheet corresponding bending angle. Parameter r_p is the punch radius which is the radius of the tip of the punch and r_m is the die radius.

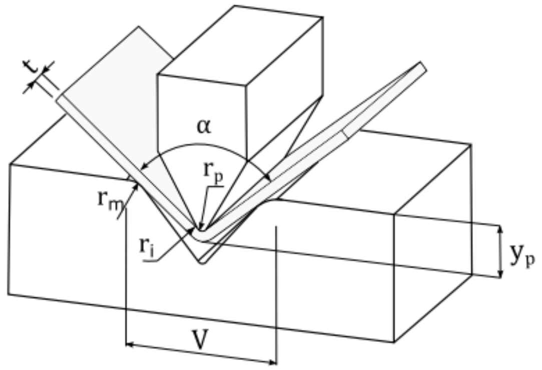

Figure 4.1: Experimental setup: sheet bending angle (α), sheet thickness (t), punch penetration (y_p), die opening (V), punch radius (r_p), die radius (r_m), inside bending radius (r_i).

In order to get consistent results, a number of constant and variable parameters were chosen. The parameters include the punch-and-die tooling made of steel where die punch had a radius (r_p) of 5 mm and and die radius (r_m) of 10 mm. The die opening V was varied between 10 and 50 mm and the punch penetration y_p was varied between 0 and 20 mm. The machine was configured to move the punch with a constant speed of 100 mm/min until it measured a resistance of 1 N. That meant, that the punch reached the metal plate and the actual bending process can start. After a hold time of 1 second the punch was moved with a slower speed of 8 mm/min until the specified punch penetration was reached. The length and width of the metal sheet was 100 mm and 20 mm respectively. The sheet thickness was varied between 0.5 and 3 mm. The constant parameters are shown in Table 4.2 and the varying parameters are shown in Table 4.1.

Parameter	**Value**	**Unit**
Punch penetration	2.5, 5, 7.5, 10, 12.5, 15, 17.5, 20	mm
Die opening	10, 20, 30, 40, 50	mm
Thickness	0,5, 1, 1.5, 2, 2.5, 3	mm

Table 4.1: Experimental setup varying parameters

Parameter	Value	Unit
Punch radius	5	mm
Die radius	5	mm
Sheet thickness	0.5, 1, 2	mm
Sheet width	20	mm
Sheet length	100	mm
Punch speed	100	mm/min
Punch speed after penetration	8	mm/min
Punch force	1	N

Table 4.2: Experimental setup constant parameters

4.1.2 | Measuring The Spring Back

The output data contained different data points, which were used to calculate the spring back. Important parameters for the calculation are the force, punch penetration and testing time. As shown in Figure 4.2 at the yp maximum the punch penetration and the force are maximized as well. The punch stays at that position for 1 second and then moves back with a slower speed. This hold time a limitation of the machine and can not be changed. After the punch is moved back, the force is reduced and the punch penetration is reduced as well, until the punch is at the initial position. For a short time after the lift, the load cell still measures a force. That is because the metal sheet springs back and the punch is still in contact with the sheet. This was measured using a python script, the green and the yellow point represent the resulting spring back distance.

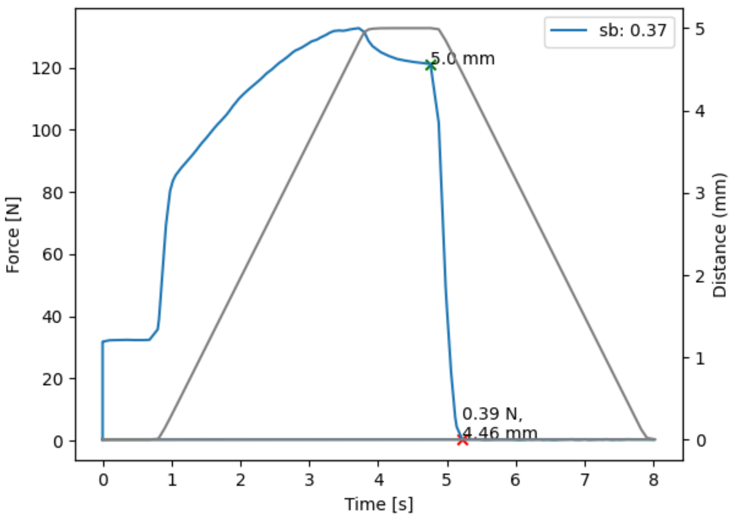

Figure 4.2: A steel metal sheet was bent with a punch penetration of 5 mm the spring back is 0.37 mm. The blue line shows the force and the blue line shows the punch penetration.

4.2 | Computational Setup

4.3 | Model Selection

4.4 | Model Training

5

Evaluation

This chapter critically examines the machine learning models conceived and partially implemented in the previous chapter. Table X shows an overview of the evaluated criteria. These are structured according to the Goal-Question-Metric approach

Mean Absolute Error (MAE) how far the predictions are from the actual output

Goal	Question	Metric
Appropriatness	How well does the model type fit the current task?	Prerequisites for model type
Correctness	Ability of the model to perform the current task measured on the development dataset and the runtime dataset	Precision, Recall, F-score
Relevance	Does the model achieve a good bias-variance tradeoff? Which means neither overfitting or unterfitting the data.	Variance of cross-validation and fit
Robustness	Ability of the model to outliers, noise and other data quality issues	Variance of cross-validation, fit
Stability	Does the artifact generate repeatable results when trained on different data?	Equalized Loss of Accuracy (ELA)
Interpretability	How well can the model be explained?	Complexity measures (e.g., no. of parameters, depth)
Resource utilization	How much resources are required to train and run the model?	Training time, runtime, storage space

Table 5.1: Overview of the goals, questions and metrics for the evaluation of artifacts following the GQM approach.

5.1 | Summary

6

Conclusions

6.1 | Revisiting the Aims and Objectives

6.2 | Critique and Limitations

6.3 | Future Work

6.4 | Final Remarks

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