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Novel approach for data-driven modelling of multi-stage straightening and bending processes

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Abstract. In multi-stage bending and straightening operations cross-stage and quantity-dependent effects crucially affect the quality of the end product. Using punch-bending units in combination with a mechatronic straightening device can improve the accuracy and repeatability of product features remarkably well. In this work a concept for an innovative hybrid model of a roll straightener in a multi-stage straightening and multi-stage bending process is proposed. This model combines data-driven elements with expert knowledge and aims to minimise residual errors of the roll straightener to reliably decrease the risk of disadvantageous cross-stage and quantity-dependent effects on a subsequent punch-bending process.

Introduction

Semi-finished wire products are usually wound onto coils for transport so that they can be forwarded into subsequent processes. One such subsequent process is punch-bending. Punch-bending mainly refers to separating and forming production processes. One or more semi-finished products, for example in the form of strips or wires made of metal, are formed and punched into a finished product on an automatic punch-bending machine in several subsequent steps. The desired change in geometry of a punch-bent part usually occurs by exceeding the yield point or altering the plastic state of a solid body. The quality of complex punch-bending parts depends significantly on the design and realisation of the multi-stage bending and straightening operations used for this purpose [1, 2].

The classical punch-bending process consists of three main stages: The wire coil, the straightener and the punch-bending unit (cf. Fig. 1). The semi-finished product is unwound from the coil and passed through the straightener. A particular challenge of the punch-bending process regarding reproducible part quality is the control of cross-stage or quantity-dependent effects that are induced in the wire in the form of bending and residual stresses as a result of wire production and wire coiling [1, 3]. Due to the alternating arrangement of the straightening rolls, the wire undergoes an elastic-plastic alternating deformation, which minimises the residual stresses and results in a flatness of the wire [1, 3]. The adjustment of the straightening process to counter these effects is carried out in industrial applications based on expert knowledge, which is problematic

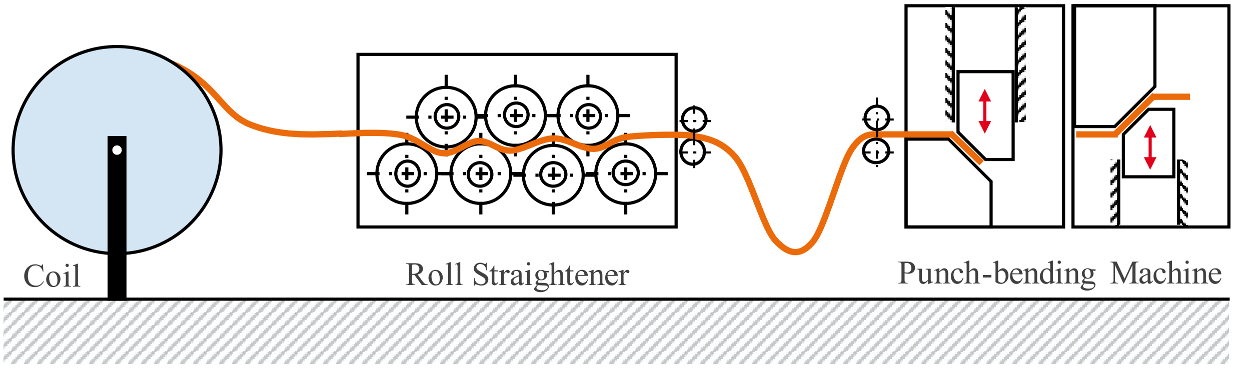

Figure 1: Schematic representation of the straightening and bending process.

due to the complexity of the interactions regarding reproducible straightening quality [1, 4]. Changes in the semi-finished product properties due to the cross-stage and quantity-dependent effects have not yet been captured by measurement technology and therefore lead to a high level of waste [1]. One approach to improve the part quality is to combine a multi-stage mechatronic straightener with multi-stage punch-bending units to create a complete mechatronic system. In order to enable targeted application, a cross-stage and quantity-dependent modelling of the described straightening and bending process and machine system is required [5].

In this article, a concept for a novel hybrid model is presented. The goal of the hybrid model is to minimise the residual errors of a roll straightener that is part of a multi-stage straightening and bending process. Therefore, a customised straightening and punch-bending process setup is presented. The introduction of a hybrid model consisting of a digital twin and a machine learning module to the demonstrator process follows. In combination with a surrogate model, a correction unit is introduced to the hybrid model which shall compute corrective suggestions for the roll straightener to minimise the residual material curvature after the straightening process. Eventually, the importance of interpretable and explainable AI is described in the context of the hybrid model.

State of the Art

Straightening and Punch-Bending Technology. Electrical connectors and terminals are typical components that are manufactured in large quantities and variants by punch-bending [6]. The high complexity and accuracy requirements of multi-stage punch-bending processes result in a high relevance of interactions with regard to component quality. These can be initiated by fluctuating properties of the semi-finished products, tools or machine tools and can significantly impair the robustness of the process [7].

Previous research work focused on the bending angle of the part to be manufactured as a qualitative parameter [7]. Accordingly, one solution approach of reproducible part quality is to record the same bending angle online in order to correct the process [8, 9]. The corrective intervention then requires a corresponding actuator system using complex correction strategies [10]. An interesting approach in the aforementioned context is the use of so-called self-correcting or mechatronic straighteners. Through mechatronic adjustment, these can achieve a significant improvement in product properties. Since a straightening process is generally used in process sequences for punch-bending strip material, this approach offers great potential in terms of optimising bending processes, provided that the necessary complex knowledge for integration within a multi-stage and quantity-dependent process is available [1, 5].

The evaluation of the complex relationships presented above is currently only possible with the help of expert knowledge and the evaluation of simulation and construction data. Process-accompanying data is also required to enable process monitoring of quality characteristics. There are still deficits in the preparation and preservation as well as the automated evaluation of corresponding information.

Modelling Approaches of Straightening and Punch-Bending Processes. In the past, several modelling approaches have been developed to optimise the straightening process, as this is essential for the part quality of the punch-bending process. These models can be divided into analytical and numerical approaches.

Henrich [11] presents an analytical model of the straightening process for sheet metal. Here, the deformation in the straightening process is represented using a bending beam with one loading and one unloading cycle. The elastic and plastic areas of the bending line are determined iteratively using third- and fourth-degree polynomials, which can be used to draw conclusions about the residual stresses, the remaining curvature and the contact forces. Another approach is to determine the contact forces and the remaining curvature by means of the straightener geometry regarding the roll radius and the roll position [12]. Paech [1] presents a simulation program that supports the determination of power requirements for process material forming. The simulation is based on an analytical model that describes the elastic-plastic alternating deformations of the straightening process.

Regarding the numerical approach, the finite element method (FEM) has become firmly established as a tool for process simulation and for analyzing the dynamics of semi-finished products, tools and machines to reduce the extent of cost-intensive preliminary tests. Regarding the straightening process, all required characteristic data such as the bending line, reaction forces or stresses can be determined. The simulation results generally correspond well with the real forming processes if unpredictable disturbances or process fluctuations such as varying material and geometric properties are only present to a small extent [4, 13].

Martinez-de-Pisón et al. [14] investigate the optimisation of the FE model regarding the straightening process using genetic algorithms. The purpose is to reduce the residual stresses after the straightening process. This approach requires a high number of simulations. Grüber [3] uses the FEM to set up a parameter study regarding flatness and minimisation of residual stresses to enable process control. For this purpose, control structures were integrated into the FE simulations to determine the correct roll feed. Regarding the punch-bending process, Mertin [15] presents a numerical analysis of a multi-stage punch-bending process. When using material with spring-back properties, the exact mapping of the material properties plays a decisive role. For this reason, a list of the influencing factors that have to be taken into account was compiled.

The presented model variants have several limitations in terms of process representation. Limitations of analytical models consist of simplifying assumptions of the material behavior to enable a mathematical representation of the complex deformation processes. These are based, for example, on the Bernoulli theory to describe the deformation of a rigid beam under pure bending stress. Furthermore, the hardening behavior is approximated, for example using a linear hardening stress-strain curve. There is also often a one-sided consideration of the isotropic or kinematic hardening model. As a result, deviations from the material properties are possible [3].

Numerical models are limited due to the high computing times, which is unacceptable for inline-capable models or iterative tool adaptions. Regarding the straightening process, these arise since material deformations occur simultaneously at several points and a segment must pass the entire straightener to adequately represent the forming process. Sufficiently fine discretisation is also required to obtain a correct resolution of the plastic deformation. This results in a high number of nodes, lines of freedom and contact points [4, 13]

AI Applications in Straightening and Punch-Bending Processes. The data generated by numerical and analytical models as well as from real punch-bending processes can be used by AI technologies to not only gain insights into the underlying physical relations between resulting product and input parameters but also to improve product quality [16, 17, 18]. For instance, a recent example is given by [17] where a convolutional neural network has been trained to predict the required stroke to bend metal sheets into a desired geometry. They additionally included Swift's law as a

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regularisation term to the loss function, therefore including domain knowledge into training. Their experiments compare the deviation of the predicted geometry after springback to the target geometry. The results of [17] show that the theory-grounded deep neural network (TG-DNN) outperforms not only support vector machines but also regular DNNs, that do not include Swift's law during training.

The use of a purely data-based model in the form of a "black box" carries the risk of an inadequate representation of the overall process due to the inadequacy of the available data to capture complex interactions in their entirety. For this reason, a pure consideration of knowledge-based or data-based models is insufficient for modelling a complex application such as the straightening and bending process [19]. To compensate for the limitations of the presented analytical, numerical and data-based model types and to combine their strengths, a hybrid model in the sense of [19] is to be developed for combined straightening and punch-bending which takes complex multi-stage and quantity-dependent effects into account. However, some of these effects are difficult or impossible to calculate or to measure. Thus, machine learning (ML) methods are required in addition to the classic approaches of analytical and numerical modelling. To the best of the authors knowledge, currently there is no publication in which a hybrid model was used for modelling the entire straightening and bending process.

Novel Concept for Data-Driven Multi-Stage Straightening and Bending Processes

The overall aim of the entire research project is to develop an explainable data-driven model for multi-stage punch-bending processes in order to make them usable in the long term, from the start of the process to the forming in the final stage. This should enable the locally limited and reproducible adjustment of process variables, e.g. roller position, number of rollers, bending punch path, tool design, in an environment characterised by a large number of disturbance variables, e.g. material fluctuations and tool wear. Due to the limited scope of this paper, however, the focus lies only on the first step of developing the hybrid model for the entire multi-stage straightening and bending process, which is the straightening process.

In Fig. 2 a schematic representation of the mechatronic, multi-stage straightening and bending process is shown. The process setup is designed for flat wire. In contrast to the straighteners used in the industry with mechanical adjusting screws, this work considers a so-called mechatronic straightener that has been developed in [20]. It consists of seven straightening rolls, in which the four lower rolls are fixed to the structure. The upper three straightening rolls can be adjusted individually in a vertical direction using stepper motors. Load cells are installed on these to record the straightening forces. Three laser triangulation sensors monitor the positioning of the upper rolls. Subsequent to the straightener, a wire buffer is required to enable a transition between the continuous wire feed of the straightener and the sequential wire feed of the punch-bending machine. In the punch-bending machine [10], the flat wire is fastened using a blank holder and then formed using the geometry of the bending punch and the bending die. At the same time, the wire is separated from the rest of the strip. An angle (α) is created in a 50 mm long piece of wire. Inside of the punch-bending unit, the bending angle is determined using an optical measuring system. Furthermore, the punch movement is monitored by an additional laser triangulation sensor.

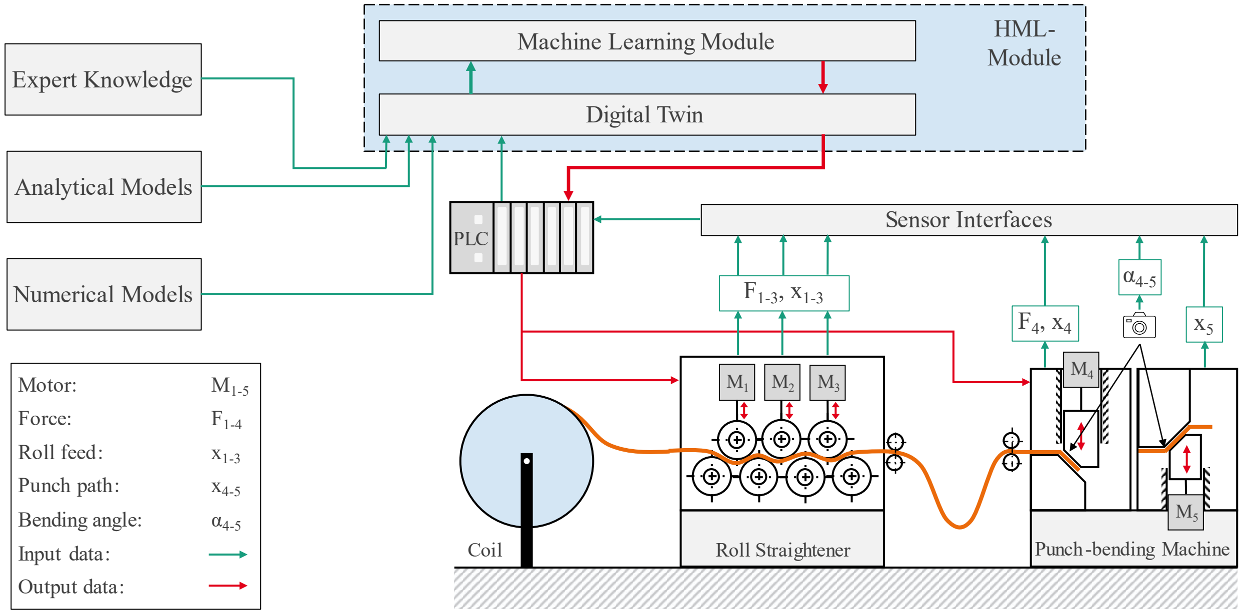

Figure 2: Schematic representation of the multi-stage straightening and bending process.

The multi-stage straightening and bending process generates data that is subordinate to multi-stage and quantity dependent effects in each stage. A hybrid machine learning module (HML-module) is thus connected to the straightening and bending process. It includes a digital twin and a machine learning module (ML-module). Via a PLC, an industrial computer with sensor and actuator interfaces, the process data is forwarded to the digital twin which is to be designed. The digital twin shall manage the generated data and forward it to the ML-module. The ML-module shall process the generated data to optimise the output of the roll straightener by suggesting actionable corrections to the roll positions of the roll straightener. Furthermore, the digital twin receives optimisation suggestions of the machine learning module and decides on whether to feed those back to the PLC. Connecting the data-driven HML-module to the multi-stage straightening and bending process results in the overall concept of the data-driven multi-stage straightening and punch-bending process.

Hybrid Machine Learning Module

The HML-module (cf. Fig. 3) represents a concept that combines expert knowledge, numerical and analytical models about straightening and bending processes, i.e. domain knowledge, with machine learning. The concept for the ML-module shows how machine learning models could process the features provided by the digital twin in three stages.

Digital Twin. The digital twin collects and manages data generated by either a simulation, i.e. a numerical model of the straightening and bending process, analytical models, the real process itself or expert knowledge. Using recorded force signals as an example, irrelevant signals are to be filtered out during the start-up phases of the process. During the running process, the force signals should then again be decisive for determining the current material condition in combination with the above-mentioned data sources. Therefore, the data has to be categorised and merged to an information model [21]. Based on the data provided by the digital twin the ML-module proposes corrections to the process**.** These corrections are then sent back to the digital twin. The digital twin thus acts as a safety measure that validates proposed corrections. One example would be filtering out suggestions that are not within the possible value range of the actuators.

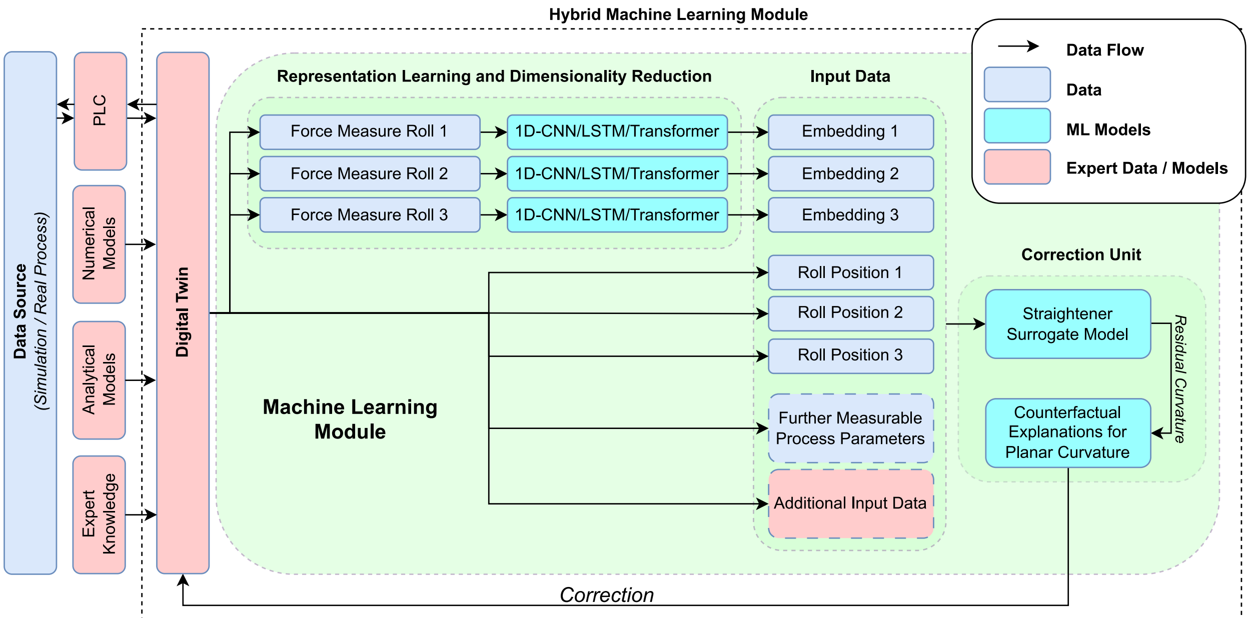

Figure 3: Structure of the hybrid machine learning module.

Representation Learning and Dimensionality Reduction. The ML-module shall receive force measurements from the digital twin which represent sequential data over thousands of time-steps and describe important material information in detail. To handle this sequential data, an embedding neural network is conceptualized into the ML-module which aims to encode quantity-dependent information about the effects of the unwinding procedure to the material [3].

Structuring the embedding network solely with fully connected layers in the neural network is not recommended, as the force measurements would induce large weight matrices which imply difficult training behavior due to high function complexity [22]. Therefore, architectures like one-dimensional convolutional neural networks (1D-CNNs) [23], Long short-term memory units (LSTMs) [24], or Transformer [25] have to be employed, each of which is able to reduce the force measurements into lower-dimensional meaningful representations, which are referred to as embeddings. For example, 1D-CNNs learn filters that produce lower-dimensional representations by extracting latent features when applied to an input [23]. The neural network in the ML-module shall contain one embedding-network per upper roll in the straightener since different material behavior has to be expected at each roll [1]. Hence, the ML-module contains three embedding-networks and therefore calculates three embeddings per product.

Surrogate Model. The goal of the surrogate model is to learn a relation between process data and the residual curvature of the material. This represents a regression problem that can be learned using neural networks or Gaussian process regression [26], for example. The input feature space of the surrogate model consists of the embedding space learnt by the embedding neural networks and the vertical roll positions of the three upper rolls in the roll straightener. Further input features for the surrogate model are conceivable. Those could for instance be the geometry of the forming tools or the horizontal distances between the rolls in the roll straightener. Due to hybrid modelling, there is an inherent possibility for the integration of domain expertise into the training of the surrogate model, thus making the surrogate model a possible grey-box-model. Grey-box-models are reported to come with the benefit of being more interpretable than strict black-box models while producing better results than simple white-box models [17, 27].

Correction Unit. Lastly, a correction unit is integrated into the ML-module. For now, it is supposed to propose corrections for the adjustable vertical roll positions of the roll straightener in order to minimise residual material curvature. However, if further process parameters such as the roll

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geometry or horizontal roll distances are included, the correction mechanism shall also be applicable to these. For this, the correction unit of the ML-module shall use the learnt relationship between the process parameters and the residual curvature of the surrogate model. Counterfactual explanations [28] allow for the definition of target outcomes of machine learning models, which they realise by altering the original input to the model. In the straightening and bending process, the desired outcome of the surrogate model is zero since a planar material, i.e. material with zero residual curvature, is expected to deteriorate the product quality after punch-bending the least. Eventually, the corrections are to be sent to the digital twin which processes and, if applicable, forwards the suggestions to the actuators of the real process or the simulation. Crucially here is that the surrogate model must learn a *meaningful* relation between the process parameters and the residual curvature. Methodologies from explainable AI can be used to investigate whether the model learned such a meaningful relation.

Taking Explainable AI into Account

Explainable AI (XAI) deals with the issue of model interpretability. Thereby, model interpretability can be understood as the degree to which a human can understand the cause of a prediction from a machine learning model [29]. Since it is planned to derive process configuration corrections using a machine learning surrogate model, the surrogate model should be investigated on whether it learned a meaningful relationship between the process parameters and the residual material curvature after straightening. A poor relationship would cause the counterfactuals, provided by the correction unit in the HML-module, to yield unsatisfactory corrections for the straightening process. To evaluate the learned relationship of the surrogate model, an empirical evaluation of the counterfactuals on whether they provide satisfactory corrections and an investigation on how the surrogate model ranks its input features in terms of feature importance is planned. A common way to quantify feature importance is to determine the so-called permutation feature importance [28, 30]. It can be calculated by comparing the differences between model errors, which are computed on the original data set and the data set in which the feature of interest is permuted [28]. Another aspect to consider is that the learnt embeddings for the force measurements are not guaranteed to be of good quality. Hence, an investigation of the embedding networks and the embeddings themselves is planned [31, 32, 33]. Embeddings should encode similar features to similar embeddings. In other words, embeddings should be robust towards small changes in the input. If otherwise, there is evidence that the embedding-networks produce non-meaningful embeddings. More explanation methods, which can depend on the chosen network architectures, are conceivable. For instance, if 1D-CNNs were used, post-hoc explanation methods such as activation maximisation [34] can highlight important input features in the force measurements.

Outlook

Future work involves not only the extension of the feature space of the presented surrogate model but also the development of analytical approaches for individual process stages. Residual stress and curvature determined by analytical models must be passed via the digital twin to the ML-module. As the modelling approach of one stage can differ from the approach for another stage, it is also necessary to investigate how different models can be combined within the digital twin. Similar to the machine learning models for the roll straightener in the ML-module, approaches have to be modelled for the process parameters of the punch-bending unit. Hereby, process parameters can be for example force measurements in the punch-bending unit, the predicted residual curvature after straightening and tool geometries. With that feature space in mind, an analogous surrogate model for the punch-bending stage that predicts the bending angle of the final product is to be designed. Furthermore, a data set has to be created by collecting simulation or real process data. This data can then be used to experimentally evaluate the HML-module. Lastly, the developed process representation is to be evaluated in terms of identifying and analysing the effects and interactions that occur within the process. This should enable an understanding of the complex multi-stage forming process as well as the design of such processes and the tools required for them.

Summary

In this paper, a novel concept for data-driven, multi-stage straightening and bending processes using the straightener as an example was developed. After an extensive overview of existing modelling approaches for straightening and bending processes, the said concept and its interfaces were presented. It combines a HML-module which integrates a digital twin and machine learning with a multi-stage straightening and bending process. Thereby, the digital twin collects and manages process data from various sources and forwards it to a ML-module. It furthermore filters out irrelevant input data from the process as well as possible incorrect actuator corrections by the ML-module. The ML-module contains embeddings networks, a surrogate model and a correction unit. Hereby, the aim of the embedding networks is to learn meaningful lower-dimensional representations for the force-measurements that encode quantity-dependent effects. The surrogate model shall learn a meaningful relationship between said embeddings, roll positions and residual curvatures after straightening. The correction unit shall use the surrogate model to adapt the actuators based on the residual curvature. In the end, methods of explainable AI were discussed which are essential to verify the ML-module on whether it learned a meaningful relation between process and target parameters, as well as methods that allow for an evaluation of the embedding space.

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