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Data-Driven Derivation of Sheet Metal Properties Gained from Punching Forces Using an Artificial Neural Network

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Abstract. The ongoing digitization of production processes provides new possibilities and potentials for process monitoring of forming and stamping processes. The component quality achievable by these processes is strongly dependent on the properties of the sheet metal material, so that a permanent digital recording of material data offers high potential for monitoring each component produced. In this context, presented paper deals with a novel AI-based method for the direct determination of material parameters from measured punching force curves. Using software systems Python and TensorFlow, an artificial neural network was first set up to determine mechanical material parameters (output data) from punching force curves (input data). As data basis for the adopted neural network, force curves were measured during punching of various sheet metal materials using a punching tool equipped with a direct force measurement device. Punching force curves were experimentally determined for the sheet metal materials DP1200, DP1000, DP800, DP600, HX380LA, DC03 and DX54. Additionally, tensile tests were performed for these sheet metal materials to determine ultimate tensile strengths (R_m), yield strengths ($R_{p0.2}$, R_e), uniform strains (A_g), elongations at break (A_t) and strain hardening exponents (n). The presented paper reveals that neural networks can accurately quantify the relationship between characteristic parameters of punching force curves and the mentioned mechanical material properties.

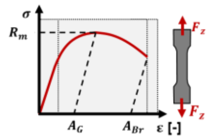
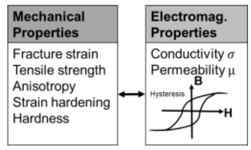
Introduction and State of the Art

Sheet metal components are usually produced via several forming and shear-cutting operations. Here, the achievable component quality strongly depends on the mechanical properties of the sheet metal material. For example, tensile strength of a sheet metal blank correlates with the probability of cracks in the part wall occurring during its deep drawing [1]. Also springback of produced sheet metal component rather depends on the yield strength and the strain hardening exponent of utilized sheet material [2]. To avoid cracking at bending radii, a sheet metal material should exhibit a high uniform elongation [3].

As investigations of the BMW press shop in Dingolfing have shown, batch-related deviations in material parameters are still one of the main causes of quality losses and process failures in the production of sheet metal components [4]. Here, the mechanical material properties can even vary over the coil length [5] as well as over the coil width [6]. Following the demand of zero-defect production, nowadays efforts are made to measure and to monitor fluctuating material properties in real-time and inline as far as possible. Inline measurement of material properties is important for the improvement of forming processes. As studies by [5] and [7] demonstrated, deep drawing processes can be controlled on the basis of inline measured sheet material properties. Here, the output of the neural network was used to control die cushion forces or active tool distances. The use of this process control resulted in a reduction of production waste.Unfortunately, most of the measurement methods used today to determine material parameters do not meet the requirements of a real time measuring system.

The uniaxial tensile test is the most frequently used offline test method for characterizing mechanical sheet metal parameters. However, a disadvantage of tensile testing is that the test specimens have to be prepared (e.g. milled) in a time-consuming and expensive way. Furthermore, the tensile test cannot be used for parallel process monitoring due to its slow test speeds. Recent research work in the field of materials testing methods actually therefore is concerned with the development of alternative, more cost-effective and/or faster test methods of sheet metal material. The following table provides an overview of existing test methods used for the recording of mechanical sheet material properties:

Table 1: Comparison of different material characterization methods

<table>
<tr><th>Tensile Test [8]</th><th>Flow curves from indenter test [9], [10]</th><th>Small Punch Test [11]–[13]</th><th>Fraunhofer IWU „materials tester“ [14]</th><th>Eddy current sensors [15], [16]</th></tr>
<tr><td>
</td><td></td><td></td><td></td><td>
</td></tr>
<tr><td>+ Simple procedure
+ Standardized

- Specimen preparation
- Destructive test
- Not inline capable</td><td>+ Simple procedure
+ Standardized

- Stand-Alone-Device
- slow
- Not inline capable</td><td>+ Simple procedure
+ Standardized

- Destructive test
- slow (2 mm/min)
- Not inline capable</td><td>+ Simple procedure
+ AI-based evaluation

- Destructive test
- Not standardized
- slow (15 seconds)
- limited inline capability</td><td>+ Inline capability
+ Not destructive

- Extensive calibration
- Sensitive to interfering signals</td></tr>
</table>

One of the new test methods is the inverse determination of flow curves from microhardness measurements [9]. However, in order to obtain reliable results from this testing method, the measurement needs to be performed without shock or vibration, so the indenter must be pressed slowly into the specimen [10]. Therefore, material characterization with indenters only seems possible on random samples outside of a running manufacturing process and thus only represents an offline measurement method. Another alternative for characterizing mechanical properties of sheet metal materials is given by the so called small punch test [11]. In this destructive testing method, a punch with a spherical face is pressed into a sheet metal specimen. The mechanical sheet material properties of the specimen material can then be determined from the punch force-displacement curve under consideration of the vertical stiffness of the test setup. A disadvantage of this testing method is the comparatively slow test speed of maximum 2mm/min [12]. Due to these slow test speeds, the small punch is also not suitable for inline material characterization. In 2021, Fraunhofer IWU introduced the so-called "materials tester" as a further testing method. The working principle of this material tester is based on the established Erichsen penetration test. During the entire measurement process, the material tester captures and records the punch force-displacement curve for several specimens in order to determine material batch fluctuations and material characteristics by means of artificial intelligence (AI) [14]. However, for inline monitoring of small sheet metal components, e.g. in stamping processes, the material tester shows only limited suitability due to the destructive measuring principle, the additional components required (e.g. gas springs) and the size of the testing device. The only testing method currently used for inline measurement of sheet metal properties in industrial applications is the multi-frequency eddy current technology [16]. The measuring principle of this method is based on the correlation between structural properties (e.g. grain size), electromagnetic properties (conductivity, permeability) and the mechanical properties of the sheet metal material [17]. To obtain the best accuracy, the eddy current probe must be located directly on the blank surface to be investigated without a gap between probe and material. Thus, an accurate eddy current measurement system requires a relatively complex hardware in order to move the eddy current probe between every press stoke [15]. Furthermore, inline material testing with eddy current sensors requires an extensive calibration process (approx. 250 tensile specimens per material). Summarizing the existing measuring methods for material characterization, these methods are either not (fully) inline capable or require relatively complex hardware in addition to the forming tool.

Since almost every sheet metal component must be trimmed or punched during its manufacturing process, it is obvious to use existing hardware in forming and cutting tools for inline material measurement. Therefore, the basic idea of the measuring method presented in this paper is to use analogies (Fig. 1) between punching force curves recorded during the manufacturing process and stress-strain curves measured by conventional testing methods for the inline material characterization. Here, the fact that three characteristic areas can always be identified in both measuring curves is exploited. At the beginning, both curves increase linearly. In the tensile test, this linear increase corresponds to Hooke's straight line. In the cutting force curve, the elastic deformation of the sheet material occurs at the beginning of the curve which is followed by the plastic flow of the sheet material. Fracture occurs in both diagrams as soon as the deformation capability of investigated sheet metal material is exhausted. Analytical correlations are known for the maxima of the two measurement curves. The cutting force maximum $F_{s\,max}$ can be calculated from the shear resistance k_s of a sheet metal material and the sheared surface A_s. The shear resistance correlates to the tensile strength R_m of the punched sheet metal material. Consequently, these correlations do allow for an analytical inverse calculation of the sheet material tensile strength from measured cutting force curves as a first approach. Similar analytical relationships (white models) for the inverse calculation of further mechanical material properties from cutting force curves do not exist yet.

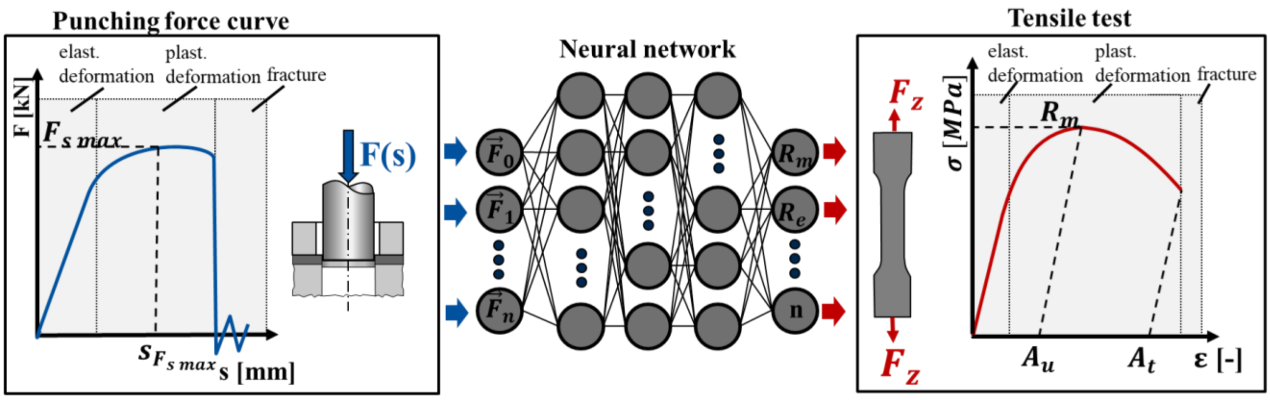


Fig. 1 Analogies between cutting force curves (left side) and stress-strain diagrams (right side) and neural network-based approach to predict mechanical sheet metal parameters from experimentally measured punching force curves (middle)

A novel approach to extract information from measured production data are machine learning (ML) strategies. Due to the steadily increasing computer performance in recent years, the availability of more data and the development of easy to use software ML strategies are becoming increasingly important in science and production. Artificial neural networks (ANN), which are in theory universally applicable and adaptable to approximate ("learn") any function hidden in structure of data, are a powerful tool of ML [18], [19]. Neural networks (NN) represent a useful variant for regression analysis [20], [21]. Therefore, the approach of the presented paper consists of using measured cutting force curves as input vector for a neural network. Subsequently, the neural network was trained on output variables, which were determined from the uniaxial tensile test. The following sections will show that the chosen AI-based approach provides a promising new method for inline characterization of mechanical sheet metal parameters.

Experimental Setup

As a basis for the training of the ANN, cutting force curves and the mechanical properties of the sheet metal materials DC03, DP600, DP800, DP1000, DP1200, HX380 and DX54 were determined. Thereby, the experimental investigations in order to record the punching force curves were performed using a modular test tool equipped with a load cell for the force measurement. The cutting speed was set to 150 mm/s at 100 press strokes per minute. The tool used in the experiments is equipped with a load cell for a direct force measurement. Such a direct force measurement can generally be used in other processes and provides transferability to other punching and cutting processes. To ensure a high resolution (60 Datapoints) of the measured punching force curves a measuring frequency of 10 kHz was chosen during the experiments. The principle structure of the tool is shown in Fig. 2 by a schematic sectional view. In the experimental investigations, all punches were firmly clamped over a length of 22mm in the shaft area. In the experiments a punch having a shaft diameter of 13mm was used according to ISO8020 standard. The punching parameters used with the test tool are presented in Table 2. The measured punching force curves are presented in Fig. 3 (left).

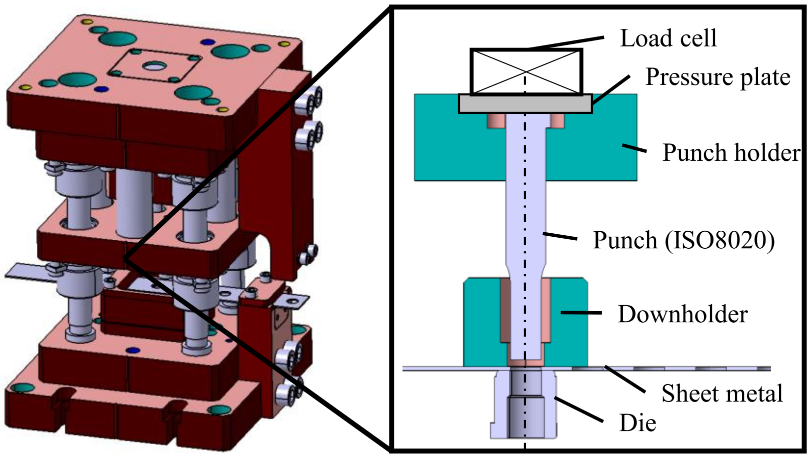


Table 2: Punching parameters

Parameter	Value
Length of punch	80 mm
Cutting clearance	15 %
Sheet Thickness	1 mm
Punch diameter	10 mm

Fig. 2 Schematic sectional view through the test tool

The experimental investigations to determine the tensile properties of the different sheet metal materials were carried out on a Roell + Korthaus RKM 100 Material Testing Machine according to DIN EN ISO 6892-1. The tensile test specimens according to DIN 50125 (H20 × 80) were manufactured for mentioned test series. The determined stress-strain curves as well are depicted in Fig. 3 (right).

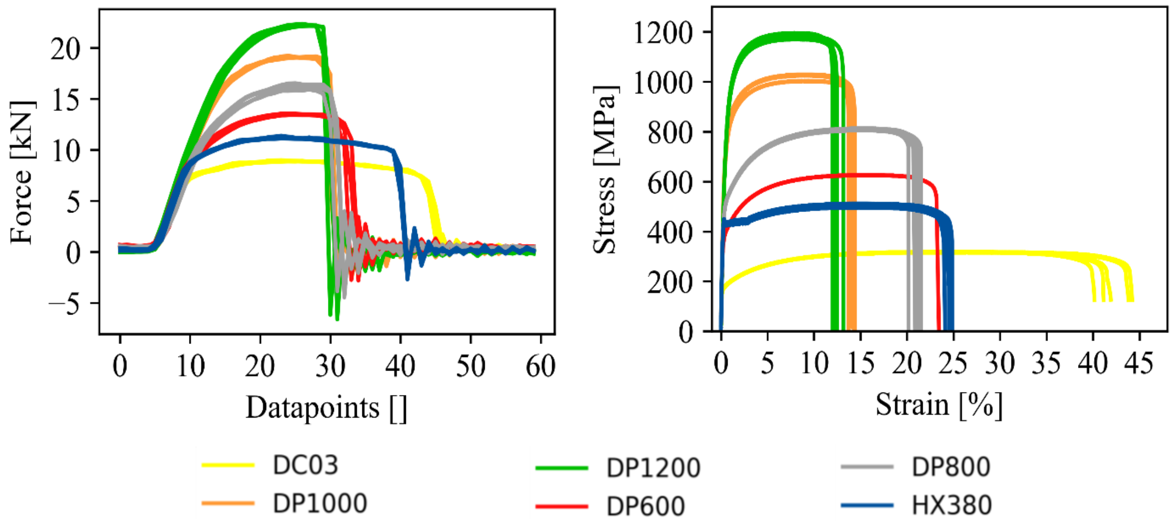


Fig. 3 Experimentally determined punching force curves (left side) and stress-strain curves (right side)

Data Preparation, Model Architecture and Training

In general, the training process of neural networks consists of reading data, preparing and (optionally) augmenting data in a specific format, creating the model itself, and running some epochs to train the model. For the investigations described in this paper on data acquisition and preparation as well as the design of ANN, the programming language Python was used. In order to correlate punching force curves with mechanical sheet metal parameters, the deep learning library TensorFlow (TF), was imported into Python. TF was developed by Google Brain, a Google research team dedicated to artificial intelligence, as an end-to-end open source platform for ML. It consists of a comprehensive, flexible ecosystem of tools, libraries and community resources for neural network design and training of neural networks. Further Python libraries used for the presented investigations are Numpy for data preparation purposes, Matplotlib for plotting and pandas for reading data from measuring protocols.

In the course of the data preparation of the present investigations, the punching force curves determined during the punching tests were initially filtered. Here, the aim was to eliminate the hardly manageable oscillations occurring in the machine structure and the tool due to the final separation of the workpiece at the end of the punching process (see Fig. 3, left). To do this, all force values lower than 4kN first were set to zero. Data augmentation represents a commonly used procedure to generate data with high diversity without special experimental effort and thus to improve the training process of neural networks [22]. Each of the measured force curves was multiplied by 20 numpy random arrays with a standard deviation of 0.5%. Therefore the amount of data or the number of measurement curves was virtually expanded. On the one hand, this was done to simulate dynamic noise that occurs in series stamping processes due to varying machine or tool vibrations and, on the other hand, to increase the variety of data for model training. Factually, additional force measurements were thereby simulated with different, virtually predefined vibrations. In total, 480 artificially vibration-superimposed cutting force curves had been generated that way for model training after this data augmentation process (see Fig. 4).

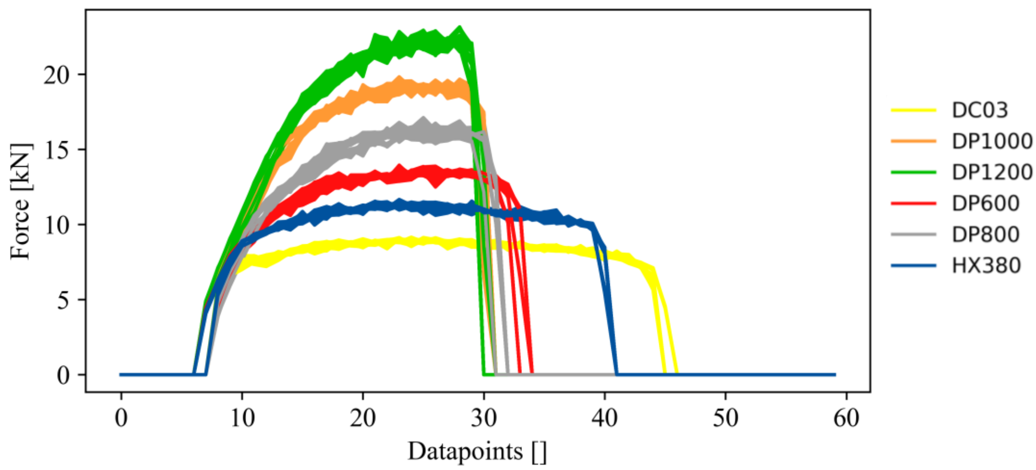


Fig. 4 Augmented training data after clipping and randomizing

A feed forward neural network (FFNN) with four hidden layers was used for the model design. Here, 64 neurons were selected for the first hidden layer of the FFNN and 32 neurons for each of the three other layers (see Fig. 5). As input for this FFNN, the augmented 60 datapoints of each of the determined and simulated force curves were used. The output vector contained the material parameters R_m, R_e/R_{p02}, A_g, A_t, and the hardening exponent n in the given order. The four hidden layers of the ANN were fully connected. The sigmoid activation function was used for the first, second and fourth hidden layer. The second hidden layer used the rectified linear activation function (ReLU). The output layer consisted of five neurons, representing the mechanical sheet metal parameters. The final network structure as well as the exact selection of activation functions was determined by a manual iterative procedure. The number of layers, the number of neurons and the type of activation function were varied until a sufficient model accuracy could be achieved (see Fig. 6 and Table 3).

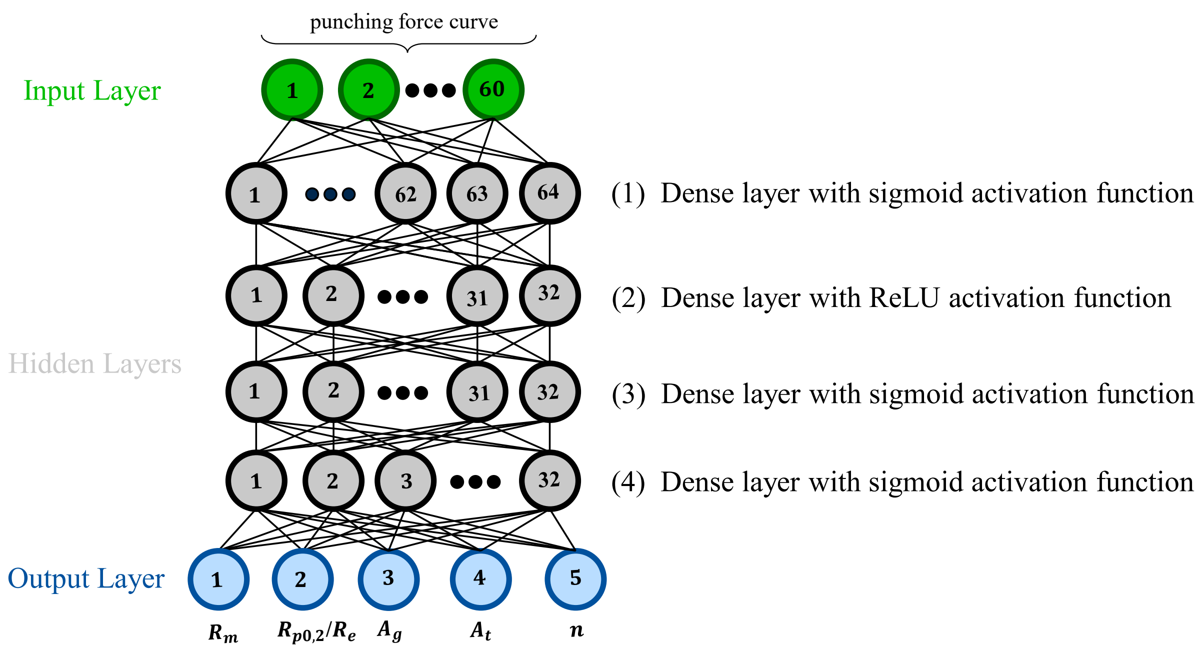


Fig. 5: Architecture of the developed ANN model

For the training cycles (200 epochs) of the created FFNN, 85% of the entire punching force curves and the associated material parameters from the real tensile tests were used as training dataset. Subsequently, this trained ANN was validated by using a further 10% of the total data set. The remaining 5% finally were used as an evaluation data set. The errors calculated during the training cycles (loss function: mean squared error) were used to incrementally improve the previously randomly initialized weights of the ANN using the Adam optimization algorithm. The progression of the loss function and the mean squared error throughout the training epochs is displayed in Fig. 6.

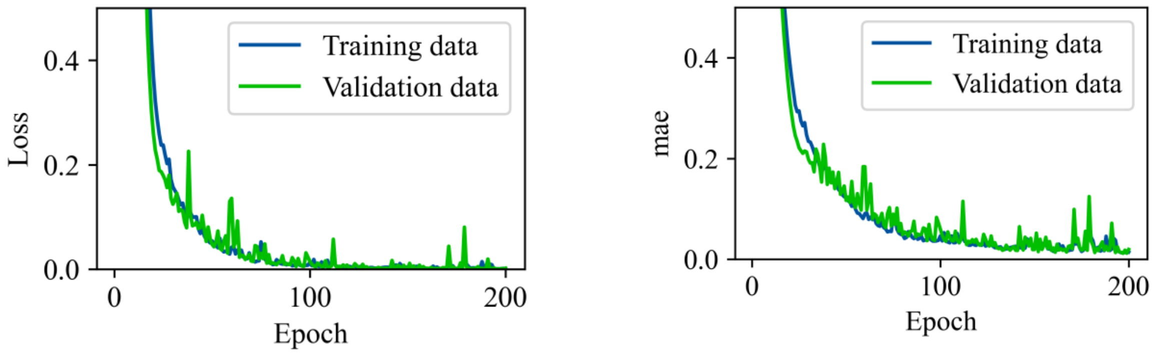


Fig. 6 Model loss (mse) and model error (mae) during training process

Results & Discussion

The objective of the presented study is to demonstrate that the regression capability of an artificial neural network can be used to obtain mechanical sheet metal parameters from punching force curves. Table 3 summarizes the overall accuracy of the neural network after 200 training epochs. Especially the metrics (mean absolute error (MAE)) after model training show, that the output of the neural network (predicted values for R_m, $R_{p0.2}/\ R_e$, A_t, A_G, and n) precisely matches to the target values derived from the uniaxial tensile test. Fig. 7 visualizes the accuracy of the trained neural network for the evaluation data set. Considering, that all data was normalized before model training, the mean average error for the predicted ultimate tensile strengths and yield strengths was calculated below 0.77 MPa. The mean average error of the predicted fracture strains and uniform strains was examined by 0.077 %, the mean average error for the predicted strain hardening coefficients by 0.0077 [-].

Table 3: Summary of the ANN metrics after 200 training epochs

	Training data	Validation data	Evaluation data
Loss (MSE)	$2.3 * 10^{-4}$	$2.2 * 10^{-4}$	-
Metrics (MAE)	$7.4 * 10^{-3}$	$7.6 * 10^{-3}$	$7.7 * 10^{-3}$

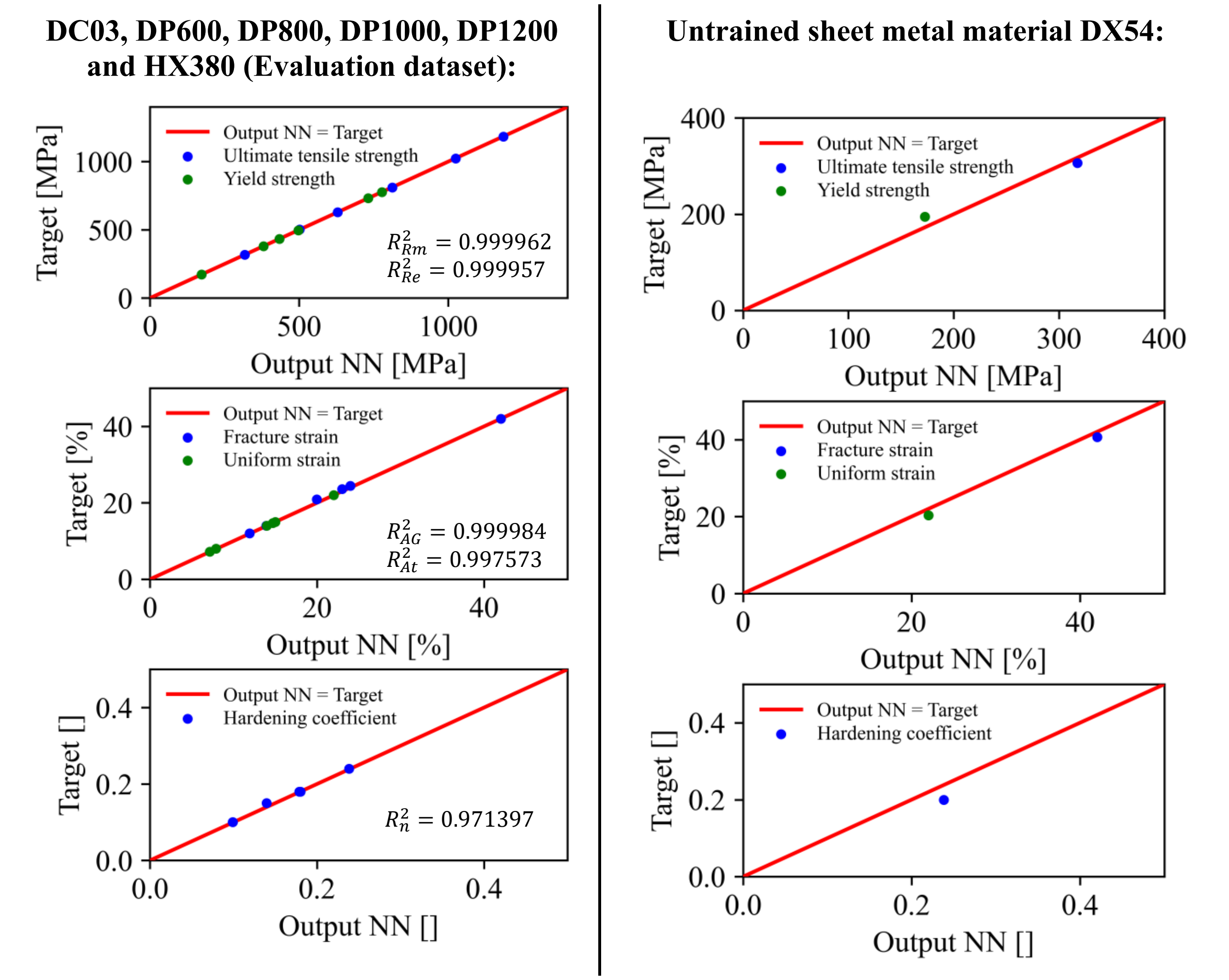


Fig. 7 Comparsion between the predicted mechanical sheet metal parameters (Output) and the targeted values from tensile tests for the validation dataset (left side) and for the untrained sheet metal material DX54 (right side).

Plots depicted in Fig. 7 (left) show the comparison between the output of the neural network and the targeted values (tensile test) for the sheet metal materials DC03, DP600, DP800, DP1000, DP1200 and HX380. The red lines in Fig. 7 represent an ideal-typical prediction of the neural network. If a predicted point is located on the red line, the prediction of the network and the result from the tensile test coincide. In order to quantify the prediction accuracy for the different material parameters, the coefficient of determination was calculated for each of the predicted sheet material parameters. For the hardening exponent a coefficient of determination of 0.97 could be achieved. The coefficients of determination for the predicted tensile strengths, yield strengths, fracture strains and uniform strains are all greater than 0.99. Due to the comparatively low mean average error of the model and the high concordance between the model output and the target values, the following finding can be stated: A trained neural network can precisely predict the sheet metal tensile strength R_m, yield strength $R_{p0.2}$ / R_e, sheet metal fracture strain A_t, the uniform strain A_G and the hardening exponent n of sheet metal materials from experimentally measured cutting force curves.

As described above, the sheet metal materials DC03, DP600, DP800, DP1000, DP1200 and HX380 were used for the training of the neural network. In order to proof the interpolation capability of the neural network, the cutting force curve of the (untrained) sheet metal material DX54 was experimentally measured and sent to the trained neural network. As Fig. 7 (right side) shows, the trained neural network was also able to precisely predict the tensile strength, yield strength, fracture strain, uniform strain and hardening coefficient of the “unseen” sheet metal material DX54.

The measured response time of the neural network to a measured cutting force curve (input vector) was 0.001s. Since the punching experiments were performed at 100 press strokes per minute, the method presented in this paper provides a new and experimentally validated approach for a highly dynamic inline measurement of mechanical material properties.

Summary & Outlook

Sheet metal components are usually produced in several forming and shear-cutting operations. The achievable component quality highly depends on the mechanical properties of the sheet metal material. Batch-related variations of sheet metal materials represent one of the main causes for defectively produced sheet metal components. These deviations of the mechanical material properties can also vary along the coil length as well as the coil width. Since the existing measuring methods for material characterization, are either not (fully) inline capable or require relatively complex hardware, a new, more practical oriented “inline” material characterization method was investigated in this paper. The idea behind this method is based on analogies between punching force curves and stress-strain curves. In particular, the approach consists of using measured cutting force curves as input vector for a neural network. The neural network is subsequently trained on output variables, which are determined from the uniaxial tensile test. From experimental investigations with the sheet metal materials DC03, DP600, DP800, DP1000, DP1200 and HX380, two key findings were derived:

- **Key finding 1:** A trained neural network can precisely predict the sheet metal tensile strength R_m, yield strength $R_{p0.2}$ / R_e, sheet metal fracture strain A_t, the uniform strain A_G and the hardening exponent n of sheet metal materials from experimentally measured cutting force curves.
- **Key finding 2:** A trained neural network can also predict the mechanical material parameters for the untrained (unseen) but similar sheet metal material DX54.

The transferability of the presented method with direct cutting force measurement to other punching tools and presses is subject of future research. These future investigations will focus on whether neural networks need to be retrained when using other sensors or presses. Future research at IFU also involves the transfer of the presented method to other sheet materials (e.g. aluminum or copper) and endurance test series to analyze the influence of punch and die wear. The application of the presented method to shear cutting processes with open cutting line (e.g. with strain gauges) will be investigated, too.

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