

Proceeding Paper

# A Contribution to the Automation of Roll Bending of Heavy Plates by Upgrading Roll Bending Machines with Artificial Intelligence †

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**Abstract:** At the current state of the art, the roll bending of heavy plates is mainly controlled and monitored manually. By automating these tasks, the economic efficiency of the process can be increased significantly. For this reason, the industry is looking for a solution to modernize the used machine tools. Therefore, in this paper, an AI-based prognosis model and an associated optical monitoring system were developed. The prediction model assists the plant operator by calculating the expected forming result. Here, it is trained with empirical process data, determined by the monitoring system. The two components were tested numerically and experimentally.

**Keywords:** bending; predictive model; artificial intelligence



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## 1. Introduction

With roll bending, plates are rounded along their length on several rotating rolls. Especially in the heavy plate sector ( $t > 3$  mm), the process covers a very wide range of applications. Here, it is used, for example, to produce thick-walled tubes and shells for the maritime sector, the renewable energies sector, and the construction industry.

A major problem associated with the roll bending of heavy plates is the high number of manual manufacturing steps. For example, the process control is carried out manually, because the used roll bending machines do not have any objective prognosis systems, that can support the plant operator in setting up the machine. Furthermore, the result control is also carried out manually. Here, templates for the target radius of curvature are used, which are held to the plate for a target-actual comparison (cf. Figure 1).



**Figure 1.** Roll bending machine (left) and result control with templates (right).

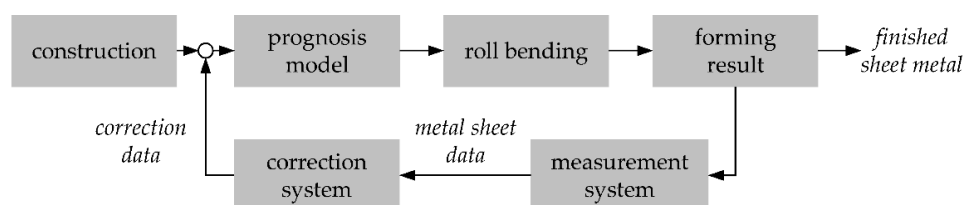
Due to the many manual manufacturing steps, the efficiency and accuracy of the process are largely dependent on the experience of the machine operator. In this context, it should be emphasized, that human errors are especially costly in the heavy plate sector, where material-intensive plates are processed in small batches. Consequently, there is great potential for optimization by automating the sub-steps of the manufacturing process. For

this purpose, there is a demand from the industry for automation solutions to upgrade the used roll bending machines. In this paper, an approach for this is presented.

## 2. State of the Art

The major challenge regarding the automation of roll bending is that the forming process is significantly influenced by stochastic effects. These mainly include batch-specific fluctuations of the material properties of the plates (strength, thickness, etc.), but also fluctuations of the properties of the machine tool (temperature of the hydraulic oil, etc.). In the case of conventional manual control of roll bending, the influence of these effects is recognized by the plant operator and compensated by an adequate adjustment of the machine. To automate the process, this task must be accomplished by technical systems.

In the past, a lot of research work has been invested in the solution of this problem. Already in 1983, Hardt [1] described the limitations of control approaches that are based solely on the prognosis of predictive models. According to his research, as shown in Figure 2, the combination of a predictive model with a measurement system is necessary in order to calibrate the model and thus to take into account the influence of stochastic effects. In this respect, the modeling complexity can be reduced by more directly measuring the forming result.



**Figure 2.** Control approach consisting of a predictive model and a measurement system.

In some studies, the approach shown in Figure 2 has already been implemented in control concepts for the roll bending of thin metal sheets ( $t < 3$  mm) [2–5]. Here, numerical models were used as prediction models. In [3,5], for example, models were used in which the sheet is discretized into rigid segments that can rotate relative to each other. The angle of rotation between the segments is calculated using a moment–angle relationship that corresponds to the elastoplastic behavior of the sheet material according to Ludwik’s elementary bending theory [6]. For the complementary measurement system, different approaches have been tested. Hardt [2] and Liewald [3] used tactile methods, where additional rollers were applied to the sheet to determine the sheet contour. Liewald [3] and Egelkamp [4] filmed the springback sheet contour at the roll exit with camera systems and determined the sheet curvature with software using edge-finding algorithms. Strassmann [5] used the fact, that the forming result correlates with the clamping force of the sheet in the roll gap and the bending force of the lateral bending roll. To measure the forces, load cells and strain gauges were implemented in the roller bearings. A fuzzy model was used to calculate the associated sheet curvature. In order to correct the calculations of the prediction models on the basis of the recorded measurement data, adaptive correction systems were used. For example, knowledge-based algorithmic controllers [3] and artificial neural networks [5] came into use.

Based on the above-mentioned research work, the establishment of fully automatic two- and three-roll bending machines for the roll-bending of thin metal sheets has already been achieved in the industry [7]. However, due to the larger dimensions, wider range of applications, and deviating machine designs (three- and four-roll systems), the adaptation for heavy plate forming is only possible to a limited extent. In the heavy plate sector, semi-automatic four-roll bending machines have only been available since 2017 [8,9]. In these, iterative FE simulations are used for the forming prediction. An AI-based correction system enables the improvement of the predictions based on process data on plates of the same batch. The disadvantage is that the forming result still has to be measured

manually. In addition, the acquisition of such a new roll bending machine requires high investment costs, whereas the manufacturing companies already have functioning and highly durable machines.

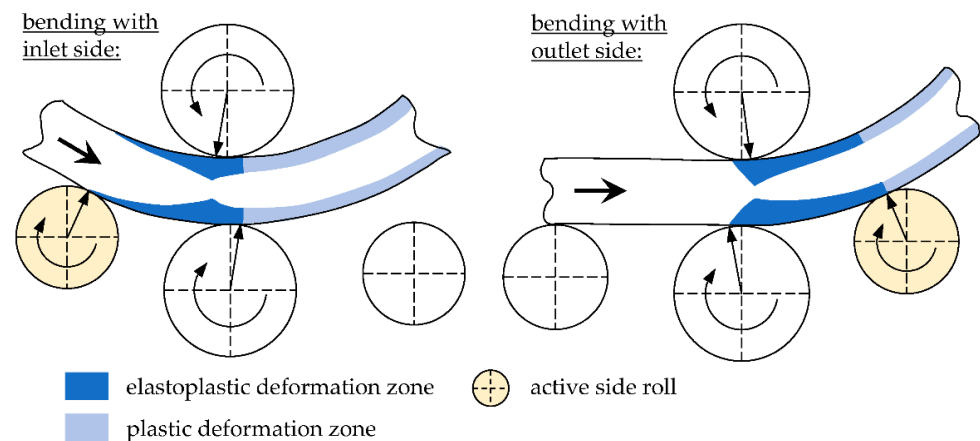
For the above reasons, there is a need for further research regarding the automation of roll bending of heavy plates. In this respect, cost-effective solutions for upgrading existing roll bending machines are of particular interest to SMEs with limited investment budgets.

### 3. Automation Approach

In this paper, an automation approach for the upgrading of 4-roll bending machines is developed. For this purpose, it meets the criteria of low investment costs, simple installation, and flexible functionality, independent of the machine size. To achieve an objectively functioning process control, the approach involves the use of an AI-based prediction model. This can calculate the expected forming result for the plant operator and thus support him in setting up the machine. Following a paper on free bending of large shipbuilding panels, the prognosis model has two layers [10]. First, a geometric model is introduced to quantify the geometric shape of formed plates. In the second layer, this model is parameterized with the help of an ANN. To generate process data for the training of the ANN, a non-contact optical process monitoring system was developed.

#### 3.1. Characterization of the Forming Process

During roll bending with a 4-roll bending machine, the plate is clamped between two centric rolls and bent locally by the infeed of a side roll. Depending on which side roll is used, a distinction is made between two process variants (cf. Figure 3): When the front side roll in relation to the rolling direction is used, this is called inlet side bending. Bending with the rear side roll is referred to as outlet side bending.



**Figure 3.** Different roll bending variants and propagation of the deformation zone.

For both variants, the mechanical working principles are shown in Figure 3. The arrows show the resulting roll forces and torques. The blue bands at the plate edges illustrate the extent of local deformation over the plate length. For both variants, the maximum deformation is reached at the contact point with the top roll. Behind this so-called bending point, elastic springback takes place, so that the amount of elastic deformation steadily decreases. At the last roll contact in the rolling direction, the amount of elastic deformation is finally zero. Behind this point, only plastic deformation occurs.

The bending variant is of great importance for the measurement of the forming result. Depending on the bending side, the area in which elastic springback takes place changes. Consequently, the area in which the plate assumes its final contour and in which the forming result can be measured also changes. Besides, it should be noted that during roll bending there is a drag distance between the point where the maximum force is applied

(bending point) and the point of complete elastic springback. This results in a delay when measuring the forming result.

Furthermore, the bending variant has a great influence on the forming result. To demonstrate this, two FE simulations were carried out using the FE model from [11]. In these, a 30 mm thick plate made of S350 was formed, whereby in each simulation a different bending variant was used. It should be emphasized that the feed distance of the side roll remained the same. The results are compared in Figure 4, which shows the distribution of the von Mises stress in the plate cross-section around the roll gap.

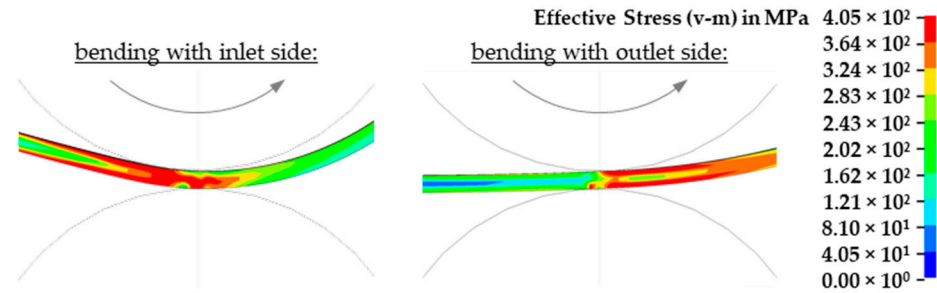


Figure 4. Influence of the bending side on the forming behavior of a plate.

Based on the red stress bands, during inlet-side bending, significantly higher stresses are achieved, especially in the middle plate fibers. Behind the contact point with the top roll, the high stresses in the outer plate fibers are reduced by plastic yielding. This results in a significantly higher deformation.

### 3.2. Geometric Model of the Plate

To quantify the formed contour of a plate and make it accessible for an ANN, a geometric model was developed. With this, the contour of a plate can be described as a function of the local radius of curvature over the plate length. Therefore, the plate is discretized into rigid segments, which can rotate in relation to each other. The angle between the individual segments corresponds to the local radius of curvature.

Figure 5 shows the procedure for the generation of the plate contour from a given function of local plate curvature versus plate length. The function is discretized into individual segments of the length  $L_0$  and the mean value of the curvature  $r_i$  is calculated in each segment  $i$ . Here, the discretization fineness determines the accuracy of the contour generation. For each segment  $i$ , a pair of two isosceles triangles with the leg length  $r_i$  and the base length  $L_0$  is formed. To create the contour of the plate, these triangle pairs are fitted into each other as a chain starting from segment 1. The triangle pair of the segment  $i+1$  is fitted into the existing chain so that the base of its left triangle overlaps the base of the last triangle. The combined contour of the bases of all triangles (black line) corresponds to the contour of the plate. This can easily be solved mathematically since the interior angles and side lengths of all triangles are known.

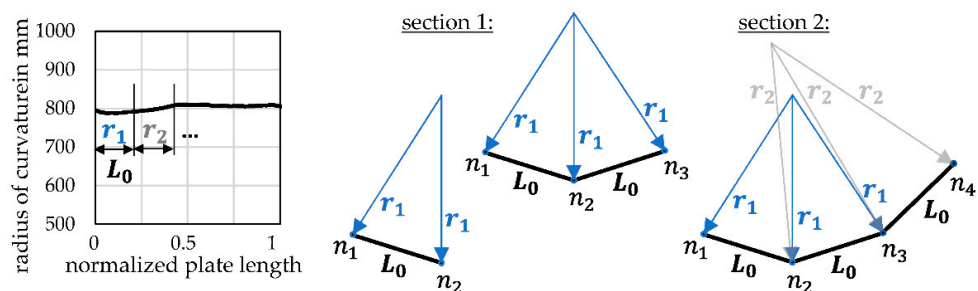


Figure 5. Principle of the geometric model of the plate.

In the reverse case, to obtain the function of plate curvature versus plate length from a given plate contour, a procedure from [12] is used. According to this, the local radius of curvature of a plate section with the initial length  $dL$  can be calculated using the strains of the compressed inner side  $\varepsilon_{in}$  and the stretched outer side  $\varepsilon_{ou}$ . With this, the inner radius  $r_{in}$  of a plate section is obtained from the following equation:

$$r_{in} = t \cdot \frac{1 + \varepsilon_{in}}{\varepsilon_{ou} - \varepsilon_{in}} \quad (1)$$

where  $t$  is the thickness of the plate.

### 3.3. Artificial Intelligence

The goal of the developed ANN is the prediction of the expected local plate curvature over the normalized plate length in dependence of defined input variables. According to [5], the basic idea of modeling with an ANN is to provide a predefined model structure with a set of data, of which the information is extracted with the help of a complex network of signal processing units (artificial neurons). The ANN can thus learn “independently” to approximate a solution for a given problem.

For accurate forming predictions, the model must consider the relevant variables influencing the forming result. In [13], it was shown by means of a numerical sensitivity analysis for the roll bending with a 4-roll bending machine, that the feed motion of the lateral bending roll, the plate dimensions and the mechanical properties of the plate material have a great influence on the forming result. As shown in Section 3.1, the bending variant is also of great importance. Accordingly, these variables shall be used as input variables for the ANN. The influence of the unpredictable stochastic fluctuations of the plate and machine properties can be detected empirically via the monitoring system and thus supplied back to the prognosis model.

For the training of the ANN, synthetic data from a FE study [13] was used. This data was obtained by analyzing 100 forming simulations executed with the software LS DYNA. In these, an outlet side bending and single rolling of a plate with a 4-roll bending machine were simulated. An overview of the used training data is shown in Table 1. The normalized plate length is an invariant input variable. The target variable of the model is the local radius of curvature of the plate, which is calculated as a function of the normalized plate length.

**Table 1.** Parameter range of the training data for the ANN.

Parameter	Type of Data	Parameter Range
plate length in mm	input	2660 ... 5250
plate width in mm	input	1400 ... 4000
plate thickness in mm	input	30 ... 100
material	input	S355, S690
side roll feed angle in degree <sup>1</sup>	input	16 ... 61.9
bending variant	input	outlet side bending
normalized plate length	input	0 ... 1
local radius of plate curvature in mm	target	-

<sup>1</sup> The feed of the side roll is specified as an angle, since the side rolls in the considered roll bending machine are fed in an arc shape.

For the training of the ANN, the dataset was randomized and divided into 70% training data and 15% validation and test data each. The Bayesian regularization algorithm was used for training. A feedforward network with two layers was selected as the network topology, with the first layer consisting of 20 neurons with sigmoidal activation functions and the second layer consisting of one neuron with a linear activation function. It was found that with this topology, a very accurate fit to the training data ( $R = 0.98$ ) and at the same time a good generalization ability can be achieved.

### 3.4. Developed Monitoring System

In this paper, a monitoring system was developed that allows the measurement of the forming result in real time. Thus, it can be used for the generation of process data for the training of the ANN. During the conceptual design, attention was paid to a simple installation, low cost, and flexible functionality independent of the machine size. Under these aspects, a non-contact measuring system based on a laser distance sensor (LDS) of the type OM70-L1500.HH1500.VI from Baumer was developed.

With the developed monitoring system, the plate curvature cannot be measured directly. Instead, it is determined iteratively with the aid of a numerical calculation routine. This essentially involves fitting a circle fit according to the Levenberg-Marquardt algorithm through defined plate points and subsequently evaluating whether this fit can match the actual contour of the plate. The radius of a verified circle fit is output as the measured value for the plate curvature.

The working principle of the calculation routine is shown schematically in Figure 6. The monitoring system measures the plate section between the points 1 and 2 marked in the figure. It should be emphasized that the monitoring system is thus primarily designed for use in inlet-side bending, since in this case almost no elastic deformation is measured. In contrast, when bending on the outlet side, the measured area overlaps the zone of elastic springback (cf. Figure 3).

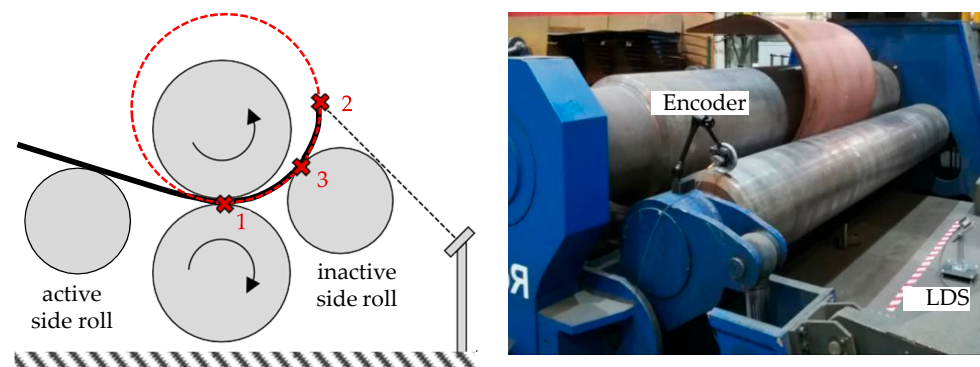


Figure 6. Working principle of the developed monitoring system.

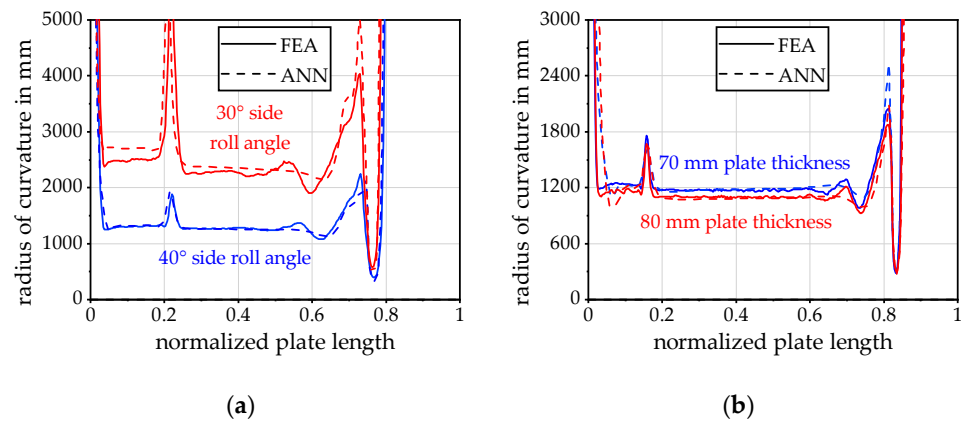
With the developed monitoring system, it is possible to measure which curvature is formed into the plate at the bending point. To be able to assign this curvature measurement to a position on the plate, an incremental encoder of the type RV3100 from ifm electronic is used. This is mounted on the side roll enabling it to measure the feed of the plate.

## 4. Numerical and Experimental Testing

### 4.1. Testing on FE Simulation Data

The accuracy of the ANN predictions was investigated using FE simulations. To this end, new parameter configurations were selected within the trained parameter range, which, however, were not part of the database used for the training. For these parameter configurations, predictions of the forming result were made with the ANN. To verify the predictions, additional FE simulations were performed.

Figure 7a shows exemplary results for two parameter configurations which differ only in the feed angle of the side roll with 30° and 40°, respectively. The simulated plate was made of the material S350 with dimensions of 3750 × 1400 × 75 mm. The curves show that the ANN was able to predict the calculations of the FE simulation very well. The continuously formed section in the middle of the plate is simulated in a very good approximation. The position and height of peaks resulting from changes in the contact state with the lateral rolls are also predicted very closely. At the plate ends, the radius of curvature tends to infinity, since these have not been formed.



**Figure 7.** Investigation of the prediction capability of the ANN for variation of (a) the side roll angle and (b) the plate thickness.

Figure 7b shows exemplary results for two parameter configurations with different plate thicknesses of 70 mm and 80 mm, respectively. This plate was also made of the material S350, whereby the length was 5250 mm and the width was 1400 mm. The feed angle of the side roll was 41.84°. Again, it can be seen that the ANN is able to reproduce the results of the FE simulation in a very good approximation. Overall, the ANN recognizes the relation that with a constant feed angle of the side roll, thicker plates are formed more strongly.

The accuracy of the monitoring system was also tested with FE simulations. For this, the FE model from [11] was used to simulate the inlet-side bending of a plate made of S350 material with the dimensions 2660 × 1400 × 30 mm. The feed angle of the side roll was 30°, 40° and 50°, respectively. Thus, low, medium, and high degrees of forming were investigated. To determine reference values, the plate curvature was alternatively determined directly on the basis of the node positions. The results of the investigation are shown in Table 2.

**Table 2.** Testing of the accuracy of the monitoring system on simulation data.

Side Roll Feed Angle in Degree	Curvature of Radius in mm		Relative Error
	Monitoring System	Reference	
30.0	2618.5	2672.5	2.0%
40.0	1089.0	1093.7	0.4%
50.0	912.1	929.5	1.9%

The results show that the monitoring system can be used to measure the forming result with a very good accuracy, irrespective of the degree of forming.

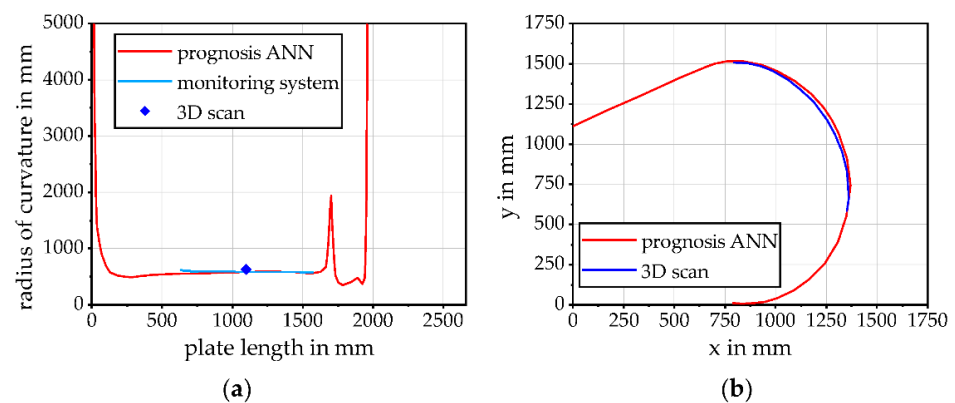
4.2. Experimental Testing

A 4-roll bending machine of the type W12-60\*4000 from the Chinese manufacturer Nantong Shengli Heavy Machine Manufacturing was used for the experimental investigation. This machine was also modeled in the numerical investigation. For the experimental study, a plate of S350 material with dimensions of 2660 × 1400 × 30 mm was formed. Since the ANN was trained with data for outlet side bending, in the experiment the plate was also formed with the outlet side. Therefore, the side roll was fed at an angle of 63.4°.

The forming of the plate was measured using two different methods. On the one hand, the developed monitoring system was used. The experimental setup for this is shown in Figure 6 on the right. On the other hand, reference measurements were carried out with a 3D laser scanner Focus 3D X 330 (Faro). With this scanner, a point cloud of the contour of a plate section was obtained. To determine the radius of curvature, with the software

GOM Inspect a cylinder was fitted through this point cloud and its radius of curvature was measured.

Figure 8a shows the comparison of the ANN prediction with the measurement results. Here, it should be noted that the ANN prediction gives the local curvature of the plate over its entire length. In contrast, only a section of the plate could be measured with the monitoring system due to the drag distance. With the 3D scanner, the measurable plate section was even smaller. The diagram shows approximately the center of the measured section for the 3D scanner. In Figure 8b, the prediction of the ANN is visualized geometrically with the help of the developed geometric model and compared to the point cloud of the 3D scan.



**Figure 8.** (a) Comparison of the ANN prognosis with the measurements of the forming result. (b) Geometric comparison of the ANN prognosis with the point cloud of the 3D scan.

According to the results shown, the ANN was able to predict the achieved plate curvature in a very good approximation. The forming is only slightly overestimated, which can, however, be advantageous in terms of a conservative process control. The deviation of the prognosis is mainly because the ANN was trained on synthetic data from a FE study. Since the model is a simplification of the reality, this method is subject to some inaccuracies. In this respect, a large influence can be assumed due to the unknown stochastic fluctuations of the plate and machine properties, which lead to deviations from the model assumptions.

For these reasons, it is likely that the accuracy of the predictions can be improved if the ANN is trained on experimental data. Based on training data on plates of the same batch, the influence of stochastic fluctuations of the plate properties can be estimated. To enable the model to differentiate between different plates and plate batches, corresponding ID numbers could be assigned and supplied to the model as additional input variables. To what extent this can improve the model predictions still needs to be investigated.

The developed monitoring system was able to reproduce the measurement of the 3D scan in a good approximation. Due to the unintended measurement of elastic deformation, which occurs when bending with the outlet side, there was a slight overestimation of the forming. However, because of the high degree of deformation, the extent of elastic springback was small. The almost constant course of the measured curve underlines the good reproducibility of the measurements of the monitoring system.

## 5. Conclusions

In this paper, a method for the roll bending of heavy plates was developed that can be used to achieve a more objective process control and partial process automation. This is done by upgrading the roll bending machine with an empirical AI-based prediction model and a monitoring system. The model can support the plant operator in setting up the machine by predicting the expected forming result. The monitoring system enables an automated measurement of the forming behavior of a plate and is used to generate process data for the training of the model. During the development, attention was paid to low investment costs, easy installation, and flexible functionality. This makes the method



particularly suitable for the upgrading of the manufacturing facilities of SMEs. With numerical and experimental investigations, it was shown that the developed components provide a good accuracy.

For a full automation of the process control, the prediction model must be extended with control algorithms that can adjust the machine based on the model calculations. It is planned to realize this in future work. Moreover, it is planned to further develop the model to reduce the required amount of process data, which will further increase its practicability. In addition, further development of the monitoring system is planned so that it can also provide reliable measurement results during outlet side bending.

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