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Transfer Learning Approaches In The Domain Of Radial-Axial Ring Rolling For Machine Learning Applications

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Abstract

Due to increased data accessibility, data-centric approaches, such as machine learning, are getting more represented in the forming industry to improve resource efficiency and to optimise processes. Prior research shows, that a classification of the roundness of shaped rings, using machine learning algorithms, is applicable to radial-axial ring rolling. The accuracy of these predictions nowadays is still limited by the amount and quality of the data. Therefore, this paper will focus on how to make the best use of the limited amount of data, using transfer learning approaches. Since acquiring data for homogenised databases is time, energy and resource consuming, logged data gathered by the industry is often used in research. This paper takes both, industrial data from thyssenkrupp rothe erde Germany GmbH and a smaller dataset of an inhouse research plant, into account. Additionally, a synthetic dataset, created by generative adversarial networks, is considered. To accomplish an improvement of machine learning predictions using accessible data, three transfer learning approaches are investigated in order to extend existing models: (I) transferring from a radial-axial ring rolling mill to a different mill containing less available data with a ratio of 20:1, (II) learning from unlabelled data using an autoencoder and (III) training on synthetic data. The obtained improvements are further evaluated. Based on these results, future possible investigations are elaborated, in particular the consideration of transfer learning from the less complex cold ring rolling process.

Keywords

Radial-Axial Ring Rolling; Machine Learning; LSTM; Predictive Quality; Transfer Learning

1. Introduction

To cope with environmental and economical requirements, techniques to increase resource efficiency in the forming industry, are applied, such as material and process efficiency [1]. Especially the reduction of parts which either need to be reworked or are scrap, is of interest. In the hot forming process radial-axial ring rolling (RARR), there are still challenges to cope with this condition, since the establishment of a stable RARR process according to GUO ET YANG is difficult and depends on many influencing factors as for instance the ring growth behaviour [2]. Hence, several approaches have been conducted to obtain these improvements, including the use of machine learning (ML) algorithms. In RARR FAHLE ET AL. proved the applicability of ML in order to predict quality, through a classification task of the roundness of formed rings after each ring roll procedure [3]. Since ML algorithms are sensitive to the data quality and data amount, predictions are still limited. The conducted survey by FAHLE ET AL. demonstrates this issue: although all considered producing companies are storing data, just 50 % of these companies are analysing and using this data [4]. Additionally, in terms of using ML for quality predictions, it is necessary to

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connect process data with its target data. In terms of predictive quality in RARR, the target data is the corresponding measured quality parameter (label). To generate data for scientific applications, this procedure is consuming time and process energy. This is especially the case, if a dataset for ML applications is needed, since the performance is depending on the data amount.

Based on the difficulties concerning data gathering and availability, this paper contributes three approaches to increase the performance of ML algorithms with accessible data using transfer learning methods. Those models are varying in the utilised datasets and their approaches of transfer learning, so that each model represents a solution for a certain issue. Therefore, an overview of possible transfer learning use cases in RARR is presented. Moreover, the concept of transferring knowledge from the related cold ring rolling process to the RARR is introduced, hence the progress of the given transfer learning methods is motivating this further step.

2. Theoretical background and related work

2.1 Theoretical background

2.1.1 Radial-axial ring rolling

Radial-axial ring rolling (RARR) is a rotary hot forming process, to shape seamless rings in order to enlarge the ring diameter, reduce the thickness and decrease the height [5]. The forming is according to ALLWOOD ET AL. obtained by two opposite radial rolls and two conical axial rolls and their synchronous feed applied on a rotating ring (Figure 1). The final ring cross section can be rectangular, or if the tools have cavities, profiled [6]. Additionally, besides the RARR there are other ring rolling techniques available, such as cold ring rolling, where the preform is not preheated and just radial rolls are used [6,5]. In RARR several errors can take place, such as ring height deviation and non-circularity [7]. In conventional mills, data is logged during the forming process for each timestep (t_i) in a defined sampling rate, including process parameters such as forces or geometrical measurements.

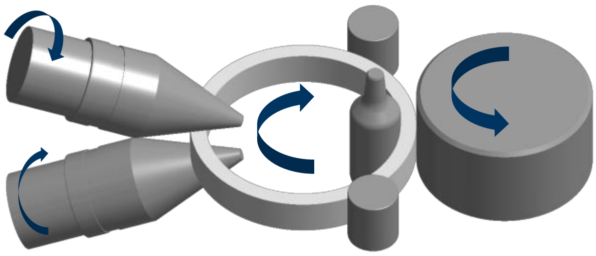


Figure 1: Radial-axial ring rolling scheme

2.1.2 Machine learning for time series predictions

In order to model time series, it is necessary to consider time dependency within the ML architecture. In the field of time series classification (TSC), where the whole timeseries is assigned to classes, multiple algorithms are according to FAWAZ ET AL. available to overcome this challenge. Those are including for instance nearest neighbour algorithms or deep learning approaches. Moreover, ensembles are available, combining different algorithms. [8] For the case of time series forecasting (TSF), where the course and future development of a time series is determined by a regression approach, statistics-based approaches and machine learning algorithms are available [9]. In terms of neural networks (NN), according to ORDÓÑEZ AND ROGGEN recurrent neural networks (RNN) can map this time dependency, trough the recurrent connection in each unit. Especially for long time scales the long short-term memory (LSTM) networks, an extension of RNNs, are usable, through a cell state, which is controlled by the activation of different gates (input, output and forget gate). [10]

2.1.3 Transfer learning

The concept of transfer learning is to improve ML models in one domain by transferring knowledge from another, but related, domain [11]. According to PAN AND YANG, it is necessary to define two spaces: the domains and the tasks. Those spaces are defined for the source and the target, whilst the source is the space providing knowledge to the target space. The domain is defined with a feature space X and its marginal probability distribution $P(X)$. The task is defined as a label space Y and an objective prediction function $f(\cdot)$. The objective prediction function is learned by the data, using training data which consist of pairs $\{x_i, y_i\}$. Therefore, the domain D and task T can be defined to:

$$D = \{X, P(X)\} \text{ and } T = \{Y, f(\cdot)\}. \tag{1}$$

Transfer learning is the case, if either the domain or the task is different between the source and the target. Within the source or target, the difference can appear in the spaces (X, Y), in the marginal probability distribution $P(X)$ or in the conditional probability distributions $P(Y|X)$ (unbalanced targets). Multiple approaches are available to obtain the knowledge transfer, such as instance transfer, feature-representation-transfer, parameter-transfer and relational-knowledge transfer. [12]

2.1 Related work

2.1.1 Machine Learning and data centric approaches in ring rolling

In the field of RARR, the CHAIR OF PRODUCTION SYSTEMS (RUHR-UNIVERSITY BOCHUM, GERMANY) recently conducted investigations in predictive quality solutions, based on ML approaches. The feasibility of a classification of the ring roundness with machine learning algorithms using process data, is shown by FAHLE ET AL. [3]. Moreover, FAHLE ET AL. introduced a model to obtain an early time series classification of the ring roundness during the process [13] and proposed methods to improve ML performances whilst using synthetic data and unsupervised learning algorithms on unlabelled data [14]. Additionally, a domain specific resample method for time scaling was provided [15]. MIRANDOLA ET AL. developed a ML model to predict the energy consumption in the RARR process using an gradient boosting approach and a multi-variable regression model [16,17]. In order to optimise the RARR process, LEE ET AL. used a combined enhanced extreme gradient boosting algorithm with a metaheuristic search algorithm [18]. Regarding quality determination with data mining methods, LAGAO classified process failures with a fuzzy logic approach [19] and GIORLEO ET AL. developed a regression model for the fishtail defect using finite element method (FEM) data [20].

2.1.2 Transfer learning

To the authors best knowledge, approaches of transfer learning have not been considered so far in RARR and in ring rolling processes. In other domains, this method has been successfully implemented in various applications [12], such as in image classifications [21] or Chemogenomics [22]. Transfer learning for image classification has been also used for classification tasks in strip rolling in order to use pre trained models [23–25]. Moreover, transfer learning has been implemented for fault diagnosis to cope with varying working conditions [26].

3. Models

In the following section, the developed transfer learning models are introduced and elaborated. The input dimension of the ML-models is set to three (amount of rolling experiments, number of timesteps, features). Since each experiment is representing one sequence, the models are limited for predictions for entire rolling time series. The focus of this work will be set on the transfer between two different mills with unequal data availability.

The models are created and trained on these datasets:

- Labelled dataset from thyssenkrupp rothe erde Germany GmbH, labels: roundness (classification) and outer diameter (regression), 1,300 experiments (TKRE)
- Labelled dataset generated by generative adversarial networks, labels: roundness (classification), 3,200 experiments (SD)
- Unlabelled dataset from thyssenkrupp rothe erde Germany GmbH, 2,400 experiments (TKRE-UL)
- Labelled dataset from an inhouse research plant of the Ruhr-University Bochum, labels: outer diameter (regression), 60 experiments (RUB).

3.1 Transferring between two different mills

To prove the applicability of the transfer from a larger database to a smaller database from a different mill, this approach is retraining a neural network model from the source space (TKRE) in the target space (RUB). This model is addressing a TSF approach. The transfer learning type is according to PAN AND YANG an inductive transfer learning approach with parameter transfer [12]. The source and target domains have the same features, but the marginal probability distribution is different since the mills are from a different type and the formed rings have different dimensions. Therefore, the domains are different but related. The source and target tasks are also different but related due to the different conditional probability distribution. The ML model is trained in the source space and reloaded for training in the target space. The initial weights of the network in the target space are taken from the source space and are retrained in the following training phases. Either all layers are retrained, or certain layers are locked and not trained.

The outer diameter (D_O), which is within the logged data, is regarded as the target in this approach. In usual cases, the outer diameter is measured continuously in conventional mills and is therefore itself not out of interest for ML predictions. Hence, this approach is addressed to prove the applicability of this method, based on this accessible target. The underlying prediction is a regression task, where the outer diameter (range: 0.3 - 1 m) is predicted for each timeseries using features from the logged data. In this first approach, just 50 % of the rolling process is considered, since this is the range where the source and target spaces are aligned concerning the rolling phases. The features are selected by their correlations in respect to the target and are *min max* scaled. Moreover, before the model training, the data is split in training, validation and test data. Within the source space, relevant processes are selected for model training according to the considered ring dimensions. The model architecture is an LSTM network to enable the mapping of the time dependency in the data. The evaluation of the performance of the model is done by the mean squared error metric. Eventually, the hyperparameters are optimised in respect to the best transfer characteristic, including the number of layers, nodes and dropout amount.

3.2 Transferring between an unlabelled and labelled dataset using an autoencoder

This model is using an autoencoder to achieve a system representation of the unlabelled TKRE-UL dataset and to use the encoder part as a pretrained model for the supervised learning within the TKRE dataset. The TKRE-UL dataset represents the source space and the TKRE dataset the target space. This transfer learning approach is according to PAN AND YANG the self-taught learning setting, which can be considered as a special case of inductive learning [12]. The autoencoder is first reducing the feature vector (encoder) and then reconstruct it back to the input (decoder) [27]. The model is therefore learning its own behaviour whilst reducing to the important feature information in the encoder part. The encoder weights are taken to retrain a model for a TSC for the determination of two roundness classes. The chosen autoencoder type is a sparse autoencoder. The network is realized, like in the first approach, with LSTM cells. Different hyperparameters are tested and evaluated, such as the minimum feature representation and the number of layers.

3.3 Transferring between a synthetic generated dataset and experimental data

The third approach consists of a synthetic data generation using generative adversarial networks (GANs) in the domain of RARR for TSC. It is investigated, if it is feasible to train a model within the synthetic data and to transfer its beneficials on experimental data. The target space is the TKRE dataset with a TSC problem and the source space is the synthetic dataset. In their work, FAHLE ET AL. used different GAN architectures for both, the univariate and multivariate time series, in the form of process data from RARR. Within the research work, unlabelled process data and also labelled data for the roundness were generated. [14] For this transfer learning approach, the labelled data is considered, and a ML model is trained on this dataset. The validation of the research results was built using the Train-Synthetic-Test-Real (TSTR) and Train-Real-Test-Synthetic (TRTS) metrics, thus a two-way view of the use of synthetic data [28].

3.4 Model Overview

The presented models are dealing with different available datasets and methodologies, so that different use cases are covered in this paper. An overview is given in Figure 2.

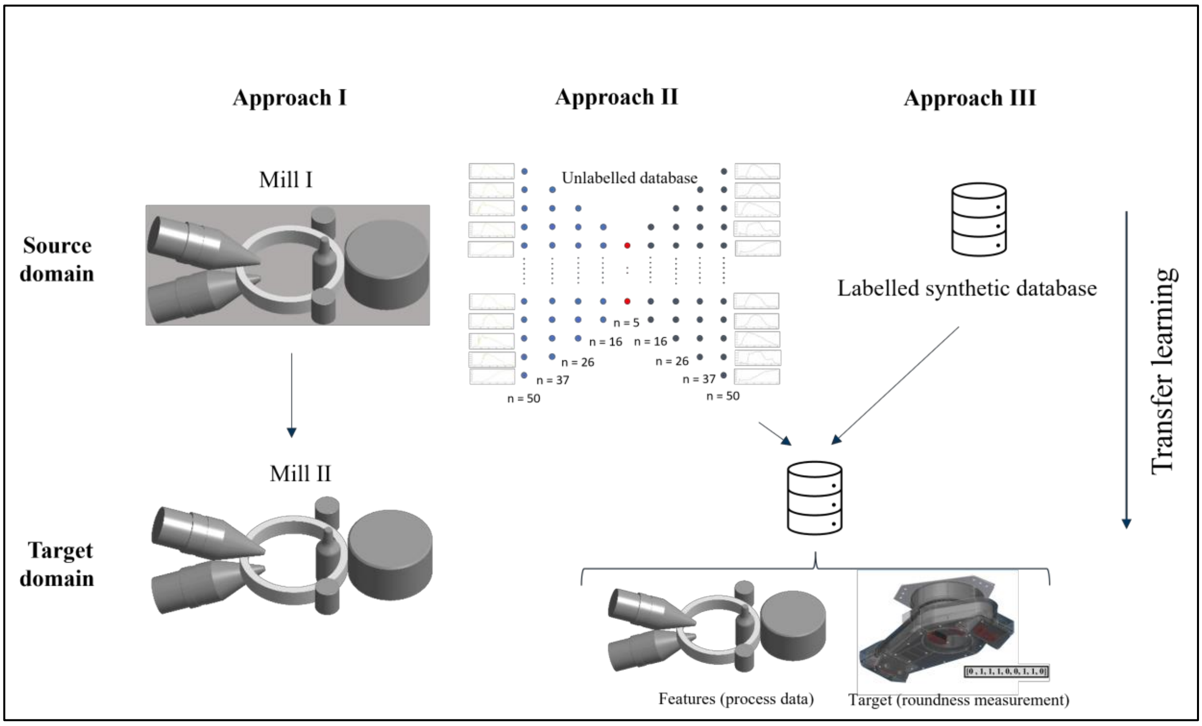


Figure 2: Transfer learning approaches for RARR

4. Experiments and results

This section is presenting the results of the three introduced models, with its focus in the approach of transferring between the two mills containing different sizes datasets. Moreover, the concept of the transfer between the cold ring rolling and RARR is elaborated.

4.1 Transferring between two different mills

The base model, trained in the source space (TKRE) to forecast the outer diameter, is tested with different layers and nodes in the LSTM-cell. The configurations and its mean squared errors (mse) are shown in Appendix 1. The lowest error is achieved by 3 layers and 7 nodes with a mse of $8.078{*}10^{-5}$ and is regarded as the baseline error. In comparison, the mse of the model trained on the smaller inhouse dataset (RUB) is greater and is equal to $1.349{*}10^{-4}$ (Appendix 2). The three baseline models with the lowest mse are used for transfer learning. In a first attempt, all layers are retrained, and then iterative layers are getting locked. The transfer learning results are shown in Appendix 3. The third baseline model (2 Layer and 7 nodes) with a retraining of all layers is leading to the best results, with a mse of $7.762 * 10^{-5}$. The achieved mse is in the magnitude of the source model and lower than the target model, trained within the RUB dataset. Therefore, it can be seen, that the transfer learning led to a significant improvement with a reduced mse by 42.5 %. As stated before, these models are covering the first 50 % of the rolling process. To extend the models for the entire process, a time scaling is needed to obtain an overlap of the rolling phases. For the entire rolling process, the mse in the target space is equal to $7.049 * 10^{-4}$ (3 layers and 7 nodes, Appendix 4). Hence, this difference is even greater compared to the difference for the first 50 %, the expected benefits of transfer learning are even greater.

Figure 3a shows the outer diameter over time out of the test dataset, with the predictions of the baseline model, the inhouse data model and the transfer learned model. Here, the transfer learned model is following the measured values best. In the validation data set, the results are showing as well better results (Figure 3b). These results are proving the transferability between two different RARR mills, with a significant improvement of prediction accuracies.

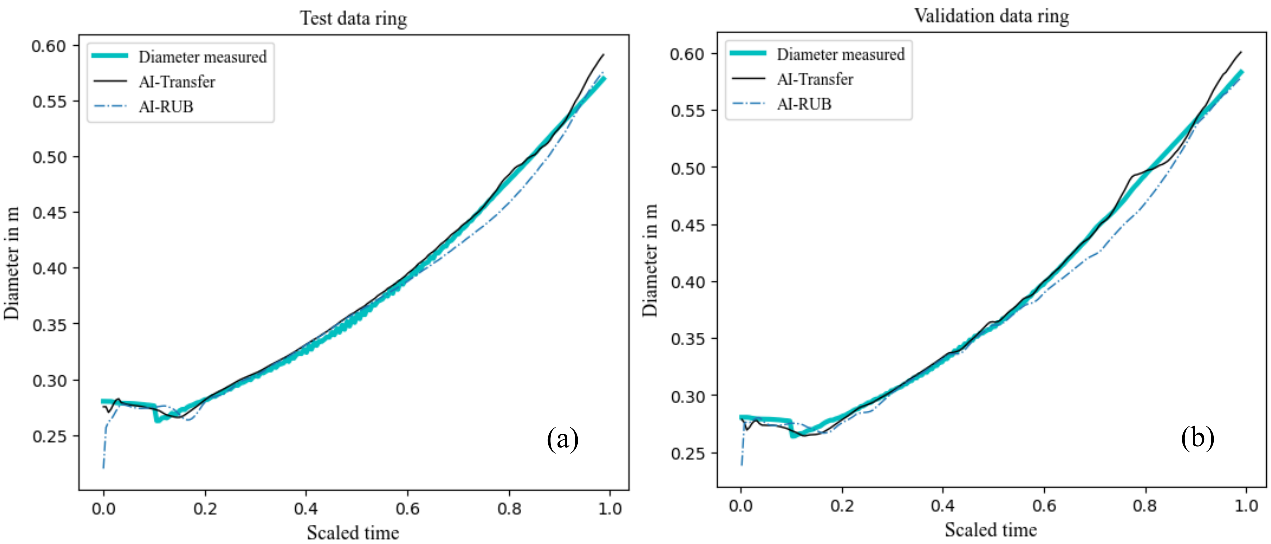
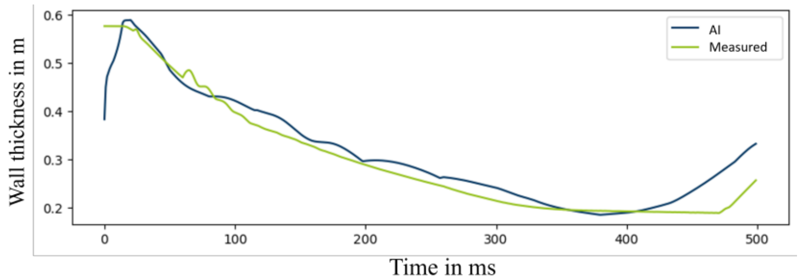


Figure 3: Excerpt of an instance rolling process of the test data (a) and the validation data (b) for the first 50 % of the process. The results of the two ML models are shown, as well the measured values (target)

4.2 Transferring between an unlabelled and labelled dataset using an autoencoder

Different hyperparameters for the sparse autoencoder are used to evaluate the performance regarding the feature representation. The final model with the best results is reducing the feature space from 50 features to 5 features within 5 layers. This configuration shows the best pest representation of the system after decoding it back to the input (Figure 4a).

(a)



(b)

Approach	Accuracy	Loss
Baseline	82,54 %	0.4335
Transfer learned	82,54 %	**0.4026**

Figure 4: Result of the autoencoder for the wall thickness (a) and TSC of the ring roundness (b)

Those layers were taken to conduct transfer learning to the TKRE-database, regarding the TSC of the roundness of the rings. To obtain this, a dense layer is added to the encoding part for a classification with this LSTM structure. The results are shown in Figure 4b. By comparing the results of the baseline approach (equal model without the pre training), the obtained accuracies are the same. Although, an improvement is seen by the loss (mse), which is 0.03 lower. This shows that the certainty of the forecast has improved with the transfer learned model, in comparison to the baseline approach.

4.3 Transferring between a synthetic generated dataset and experimental data

To validate if the synthetic data can be used for beneficial transfer knowledge, FAHLE ET AL. conducted a survey with nine process experts in radial-axial ring rolling. The results showed that several process experts were already unable to distinguish the synthetic from real process data. The evaluation of the results was based on the well-known inception score and the hype metric [29,30]. An instance of two rolling processes for the conducted evaluation is presented in Figure 5.

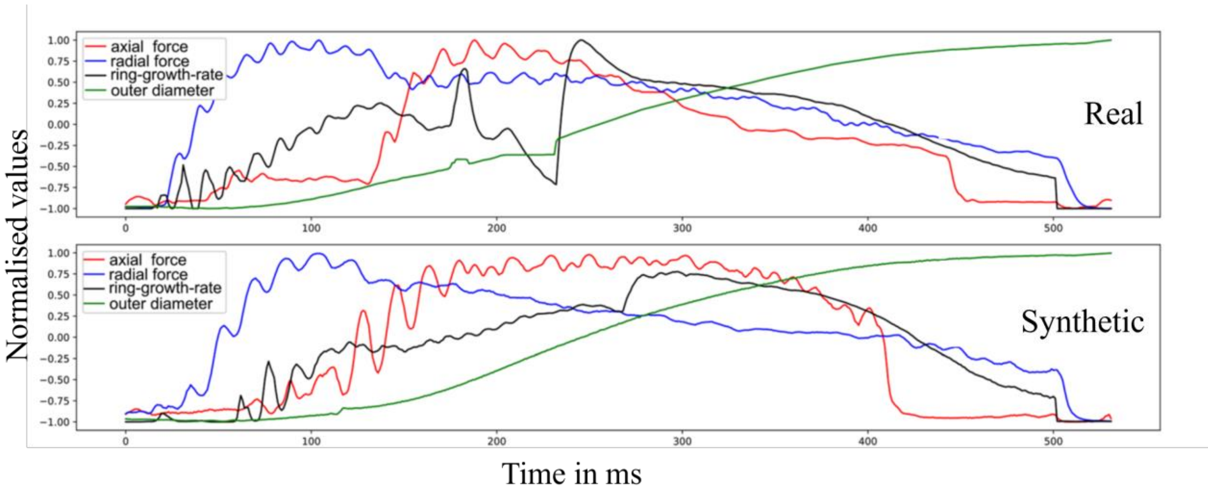


Figure 5: Instance rolling process for the evaluation of process experts [14]

Within the consideration of TRTS, especially promising results with a high accuracy of up to 97.4 percent could be achieved with the univariate use of the radial force. In addition, the basic usability of training a ML model was also demonstrated, with multivariate generated data and the TSTR metric. This is important for the productive usability, such as training exclusively on synthetic data and transfer learning it to real-world data since this data can be created in a few seconds with millions of copies. This model was able to achieve a significantly higher accuracy in the target space (TKRE dataset) than the random decision. [14] The exact improvement for the classification accuracy needs to be quantified in further investigations. In summary, the approach taken by FAHLE ET AL. to transfer synthetically produced data to real-world data is a promising approach and the basic feasibility of the approach has been demonstrated.

4.4 Concept of transfer Learning using cold ring rolling data

The DFG-project Nr. 499350001 (funded by the DFG-German Research Community) is currently expanding the given ideas of transfer learning further to a different process - the cold ring rolling. The cold ring rolling is a seamless ring forming technology at room temperature, containing only radial rolls and is forming smaller rings sizes than the RARR [5]. The shape of the ring is only constricted by its tool geometry and the radial feed. This process has two major advantages and is therefore considered: The dimensions of the shaped rings are smaller, and the process is carried out without pre heat treatment of the ring. This is reducing the consumed energy as well as the shaping- and preparation time. In a first step, the applicability of ML in cold ring rolling will be evaluated.

Due to the simplification of the regarded rolling process, it is possible to generate a database using an experimental setup, determined by a design of experiments (DoE) with the data amount needed for training ML algorithms. The scheduled scope is in the order of magnitude comparable to the utilised industry data in this paper. To meet the requirement of a balanced data set regarding its target values, the experimental database will be extended by synthetic data, mainly gathered by simulations. Those simulations are used for enriching the database, but also to address process controls reproducing errors, to homogenies the target classes. The synthetic data will be generated using these approaches: FEM, semi-analytical models and synthetic data generated by GANs shown in this paper. The FEM data will be generated using three approaches according to ALLWOOD ET AL.: models in pseudo-plane strain, partial ring models and full ring models [7]. Since FEM is time consuming (multiple hundred CPU hours), there is currently a semi-analytical model in development. The model is aiming to combine numerical algorithms and analytical approaches and is based on prior investigations of BROSIUS ET CWIEKALA, applying a semi-analytical model on the deep drawing process [31]. This complementary database, combining experimental and synthetic features, designed for ML-applications, is expected to perform more accurate compared to recent models in RARR. Therefore, it seems feasible to pre-train a ML model within this database and transfer it, similar shown to the transfer learning between the two RARR plants presented in this paper, to the radial-axial ring rolling data.

5. Conclusion and future work

In this work, three transfer learning approaches in the domain of radial-axial ring rolling were presented. It is addressing cases where no sufficient data amounts are available, or high accuracies are required. These approaches are transferring knowledge from these sources: a different mill, unlabelled data and from synthetic data generated by GANs to target spaces with less available data. The feasibility of the transfer from the synthetic data and the unlabelled data with an autoencoder is shown. The transfer using a pre-trained model through an autoencoder is not improving the accuracy but is reducing the loss and therefore the certainty of the prediction. The transfer from the synthetic data is showing promising results on univariate time series. Especially the transfer between two different machines, from the mill with the higher data amount to the minor one, showed significant improvements. The transfer learning lead here to a reduced mean squared error of 42.5 % compared to the model without transferring.

This work contributes approaches to implement transfer learning, if the accessible data amount is not sufficient, but related data from other machines or unlabelled data is available. Moreover, it shows the possibility of generating data by GANs, if no other data is available. These approaches can be considered in further scientific investigations, but also in industrial applications.

In further investigations, the proposed model for transferring between to different mills should be extended for the entire ring rolling process by aligning the rolling phases and can be applied to relevant process errors, such as ring climbing. Furthermore, it can be applied for time series classifications, like the ring roundness. Regarding the autoencoder and synthetic data approach with the generative adversarial networks, greater databases can be considered to improve given accuracies further. The present progress achieved by using transfer learning concepts, motivates even more extensive approaches, such as transferring from the less complex cold ring rolling to RARR. This question is currently considered in ongoing research (DFG Nr. 499350001).

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Appendix

Appendix 1: Mean squared errors for given hyperparameter configurations for the prediction of the outer diameter within the TKRE dataset. The chosen baseline models with the lowest mse are highlighted

Layers	3 nodes	5 nodes	7 nodes
1	$1.788*10^{-4}$	$1.512*10^{-4}$	$1.184*10^{-4}$
2	$1.665*10^{-4}$	$1.457*10^{-4}$	**$1.074*10^{-4}$**
3	$1.408*10^{-4}$	**$1.065*10^{-4}$**	**$8.078*10^{-5}$**

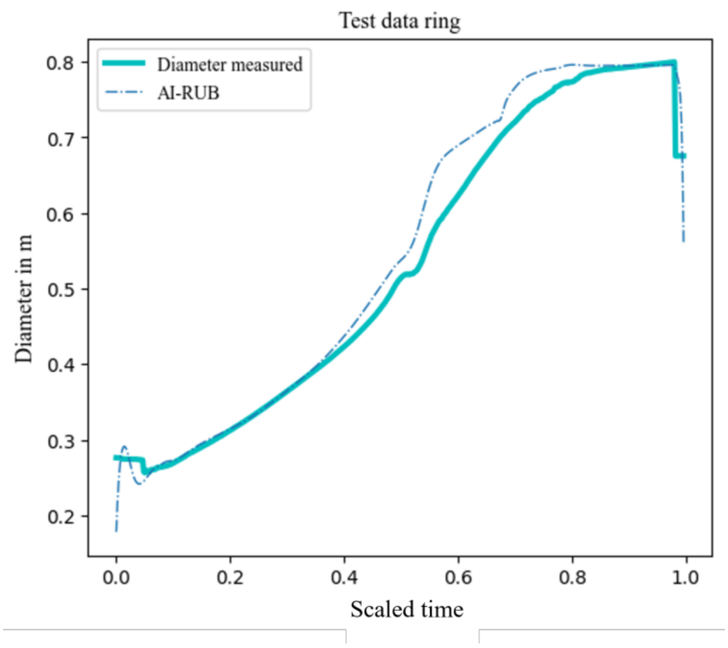
Appendix 2: Mean squared errors for given hyperparameter configurations for the prediction of the outer diameter within the RUB data set

Layers	3 nodes	5 nodes	7 nodes
1	$2.264*10^{-4}$	**$1.349*10^{-4}$**	$1.373*10^{-4}$
2	$3.647*10^{-4}$	$2.058*10^{-4}$	$1.362*10^{-4}$
3	$3.009*10^{-4}$	$1.617*10^{-4}$	$1.571*10^{-4}$

Appendix 3: Mean squared errors for transfer learned models. The retrain layer indicates the layer from which layer on weights are getting retrained

Retrain layer	2 layer 7 Nodes	2 layer 5 Nodes	3 layer 7 nodes
0	**$7.762*10^{-5}$**	$9.483*10^{-5}$	$7.871*10^{-5}$
1	$1.088*10^{-4}$	$2.006*10^{-4}$	$8.361*10^{-5}$
2	$8.087*10^{-4}$	$6.869*10^{-4}$	$1.437*10^{-4}$

Appendix 4: Excerpt of an instance rolling process of the test data for the entire ring rolling process



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