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Investigation Of Suitable Methods For An Early Classification On Time Series In Radial-Axial Ring Rolling

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Abstract

To increase competitiveness in the hot forming sector, there is a constant urge to improve the rolling process and its products. Industry 4.0 and its impact on data acquisition and data availability enable data driven methods for optimization. In order to optimize the quality prediction of rolled rings in Radial-Axial Ring Rolling (RARR) with regard to ovality as early as possible and hence prevent scrap and unnecessary rework, machine learning methods from the early classification on time series subdomain are used and evaluated within this research. Different approaches from the time series classification domain within supervised learning are used and compared. A so-called minimum prediction length of the ring rolling process time series is analysed using real world production data from thyssenkrupp rothe erde Germany GmbH. Building upon results of earlier research regarding the use of time series classification in RARR by FAHLE ET AL. fully automated as well as domain specific minimum prediction lengths will be investigated. The results of both approaches are compared and evaluated with regards to the current maximum prediction accuracy using the whole sequences, which should provide the highest score as it holds all available information of each sample.

Keywords

Radial-Axial Ring Rolling; TSC; ECTS; Quality

1. Introduction

Preventing scrap and unnecessary rework is a difficult task in many areas of manufacturing. In Radial-Axial Ring Rolling (RARR), production times vary depending on the rolled geometries. Smaller rings with an outer diameter smaller than 1.5 m may need production times less than one minute on the actual ring rolling machine and can be rolled within one heat. Rings with diameters of up to 16 m however need several minutes divided in different heats. For this process, current RARR machines log several channels during the forming and give access to high dimensional information including forming forces, torques, geometric features within the forming process and many more. All those information can be interpreted as a fixed sequence for each rolled ring and thus can be analysed using methods from machine learning. Every sample (representing a single rolled ring) used within this research was measured after the production process using an automated 3D-laser measurement unit, producing accurate targets regarding the ovality of each ring. This combination of logged channels (features) and measured ovality (target) allows the utilization of supervised machine learning methods. Within supervised machine learning, there is the domain of time series classification (TSC), where time series such as the logged channels are used to predict a continuous or discrete label. For the underlying task of predicting ring quality, a discrete label approach is chosen. A general introduction and brief definition of TSC and time series is given.

According to FAWAZ ET AL. and specifications given by FAHLE ET AL. regarding RARR the TSC-task can be formulated as followed: An univariate time series

$$X = [x_1, x_2, \dots, x_T] \quad (1)$$

is a timestamp ordered set of real values with a fixed sampling rate. The length of X is equal to the real values T depending on the individual rolling time of each ring. Each univariate time series represents a logged channel of the RARR process. An M-dimensional multivariate time series

$$X = [X^1, X^2, \dots, X^M] \quad (2)$$

consists of M different univariate times series with $X^i \in \mathbb{R}^{\mathrm{T}}$. A dataset

$$D = \{(X_1, Y_1), (X_2, Y_2), \dots, (X_N, Y_N)\} \quad (3)$$

is a collection of corresponding pairs (X_i, Y_i) with X_i either being a multivariate or univariate time series and Y_i as its target variable vector. For now, the classes are defined as a binary classification task of either "no ovality" or "ovality" [1,2]. This data set can then be used for a supervised learning task to find a model that learns a function that maps the input sequences to a class label [3]. For more in depth information, a great introduction to the different problem definitions using machine learning in the domain of sequence data and its variants is given by LONING ET AL. [4].

A working TSC model for the application in RARR does provide several advantages such as a cost-efficient post-process labelling of product quality regarding the used threshold for its training data. If the model is sufficiently accurate and precise, this can lead to an alternative way of predicting quality instead of measuring it for every single sample whilst only measuring those that were predicted to be of bad quality and thus save production and energy costs. Other benefits of such a TSC model are several techniques such as a class-activation-map (CAM) which visualizes the decision of the model to show what neuron is firing given each time step within the sequence [2]. However, TSC holds one negative effect, which is the post-process prediction of each label, i.e. the rolling process has to be finished before a prediction of the quality (ovality) can be made by the used model. This does only allow for a prediction and not for a prevention of the regarded quality aspects. Extending the model to prevent bad quality, a prescriptive approach has to be implemented. This can be done by using models and methods of a subdomain called early classification on time series (ECTS) that seeks to classify time series as early as possible while not neglecting the prediction accuracy. In contrast to the approach of labelling a full time series with a label, there is the challenge of classifying a time series as early as possible. Thus, this approach tries to classify time series with less time steps than the TSC approach and therefore is generally a more difficult task to provide sufficient or equally accurate results according to MORI ET AL. [5]. A more in depth and detailed definition of the ECTS approach is given by XING ET AL. and MORI ET AL. [5,6].

In the following section, a short summary of the basic domains i.e. RARR, TSC and ECTS is given by presenting related works in form of current research and industrial advances in each domain.

2. Related Work

The following section covers the related work in the domain of RARR and the two subdomains of the machine learning domain: TSC and ECTS. Current research and state-of-the-art algorithms will be discussed and presented to give a broader overview of the research focus within this experiment.

2.1 Radial-Axial Ring Rolling

Many approaches concerning current research within the domain of RARR are dealing with FEM-Simulation, quality issues and process improvements. For example ALLEGRI ET AL. proposed new milling curves that achieved good quality results with reduced process time and loads based on a FE-Simulation [7].

An innovative control strategy for titanium alloy based on an intelligent FE-simulation is introduced by LI ET AL. to prevent damage to the microstructure of the titanium alloy by controlling its temperature [8]. Enhancing this approach, LIANG ET AL. used an intelligent FE-simulation to plan rolling paths for the ring rolling process of titanium alloy [9].

Process improvements and new and innovative ways to combine RARR with other processes are researched as KUHLENKÖTTER ET AL. investigated the suitability to combine the RARR process with thermal spraying to compact coatings in an innovative manner. Yet a final intact coating could not be established in the initial experiments, promising results, showing that by the subsequent rolling of thermally sprayed coatings the porosity can be significantly reduced and higher compressed residual stresses can be induced, are presented [10]. Another approach where RARR was combined with a different process is shown by MICHL ET AL. by using additive manufacturing in form of a wirearc additive manufacturing. The authors explored whether wirearc additive manufacturing is a suitable solution to produce better near-net shape pre-forms. Referring to their results, wirearc additive manufacturing shows promising results to lower process expenses and improve process efficiency [11].

An overview of the advantages of data driven techniques in metal forming as well as remaining research questions are given by HAVINGA ET AL. such as model uncertainty and measurement accuracy in metal forming [12]. Research regarding machine learning for quality prediction was conducted by different authors. GIORLEO ET AL. used a regression model based on process parameters from FEM data to classify product quality with regards to the fishtail defect [13]. A different form error prediction using machine learning was researched by FAHLE ET AL. regarding ovality. The authors investigated the data utilization and data analysis methods in RARR in 2019 for a variety of German ring rolling companies [14]. Moreover, they used a TSC to classify real world production data to improve the process quality and focused on different preprocessing approaches [1]. This TSC approach will be enhanced throughout this study and the current related work for the domain of TSC and ECTS will be lined out.

2.2 TSC

During recent years, many models and algorithms of different types have been proposed and a comparable data base for validated comparisons was established by introducing the UEA & UCR Time Series Classification Repository [15]. This database was the baseline to validate a variety of models such as HIVE-COTE: a big ensemble with great results on the repository [16]. A big effort was taken by BAGNAL ET AL. in their review of current advances regarding TSC algorithms where a variety of current algorithms was evaluated and compared [17]. Nevertheless, deep learning approaches, which have gained great popularity during the last decade due to their advances in image recognition and other areas, have not been the focus of the review. However, several deep learning approaches to solve TSC tasks have been proposed such as InceptionTime that bases on an Inception architecture [18] or another approach combining the convolution based structure with long short-term memory cells in a so-called MLSTM-FCN network architecture [19]. During the last years several approaches have been taken to form unified architectures for the TSC task, one of those is sktime by LÖNING ET AL. which is compatible with the famous scikit-learn python library and presents a unified interface to deal with time series [4].

2.3 ECTS

SANTOS ET KERN investigated different approaches for the early classification on time series and many agreed on the definition that a classification decision should be made as early as possible while the classification accuracy should not be sacrificed too much. They further investigated different approaches and already included deep learning approaches to solve the ECTS problem [20]. Another recent systematic review for ECTS was published and reviewed different ECTS approaches for many different domains such as Human Activity Recognition, Industrial Process Mining, Quality Monitoring and others [21]. A fairly new approach is proposed by SCHÄFER ET LESER named TEASER. TEASER uses a two-tier approach where a slave-master structure is established to find the best individual decision times for an early classification. The slave classifier classifies the time series and computes class probabilities which are then passed to a master classifier that decides whether the probability is sufficient to emit a final classification result [22]. Another approach that focuses more on the multivariate aspect in ECTS is a confidence-based approach by HE ET AL. Within their research they focus on a multivariable and interpretable approach based on interpretable rules mined from the time series and using subsequences [23]. Moreover, ECTS is used in a variety of different domains. It is used by HATAMI ET CHIRA to classify odor in the bio-chemical domain. They use an ensemble to agree on either accepting or rejecting the class label. The authors use their implementation as the core mechanic for their online e-nose system for odor classification [24]. Moreover, it is applied to other real world datasets within the UCI machine learning repository such as the hydraulic system monitoring data set. One example is the divide-and-conquer-based approach by GUPTA ET AL. [25] or other applications of ECTS such as semiconductor manufacturing [26,27].

3. Experimental setup

The following section describes the essential parts of the later conducted experiments namely the data set all experiments are based on, the preprocessing steps and the used models and approaches.

3.1 Data set

The used data set for this research is provided by thyssenkrupp rothe erde Germany GmbH and is part of its real world production data of different production days. The used samples represent a mixture of different geometric preforms and rolled shapes. New production data is constantly added and preprocessed but the state of the current data set consists of 1078 multivariate samples. Due to a non-disclosure agreement the dataset must not be made available to public. The data set is almost evenly distributed as the threshold for the quality prediction was set to in internal standard to enable a working model to increase production quality by a sufficient amount. The data is acquired at thyssenkrupp together with their representing targets acquired by an independent measurement unit. The multivariate channels/features of the dataset range from radial and axial forces, ring growth rates, motor current and several geometric features of the process. The used data set is split up into a train and test split using an 80/20 split ratio to prevent information leakage. Moreover, a five-fold shuffle split validation is performed for more reliable classification results on the domain specific approach.

All data samples were backpadded to ensure an equal length as process variations lead to different length time series. Backpadding was used because of the requirement that this model is intended to be deployed in a real world radial-axial ring rolling mill system and predicting ovality as early as possible to enable counter measurements. Thus, a backpadded approach is used because the incoming time series length of the process is not known prior due to the different preforms and rolled geometries. Moreover, a second preprocessing is used to the extent that a specific logged channel represents the current rolling phase that the process is in. This channel was used in earlier research by FAHLE ET AL. [1] to investigate suitable preprocessing methods for the application in RARR. Figure 1 depicts an idealized trend of the ring rolling process and its respective rolling phase. The preprocessing that is done in this research in addition to the single backpadding is a cutting between phases, meaning that all samples were separated in four different data sets each containing the samples up to the different rolling phases (e.g. Start,…, End Phase 1; Start, …, End Phase 2; etc.). This is done to investigate a minimum predictive length for the ECTS approach in combination with necessary process specific counter measurements that need to be performed at specific times in the process as they cannot be implemented in every step of the process.

In addition, all samples, neglecting their earlier preprocessing, were examined using standardization, with a scaler fitted on training samples only to ensure no information leakage into the test set, or their raw input values with no standardization. All these preprocessing steps are performed to ensure an early classification as well as ensure system specific requirements due to the process nature.

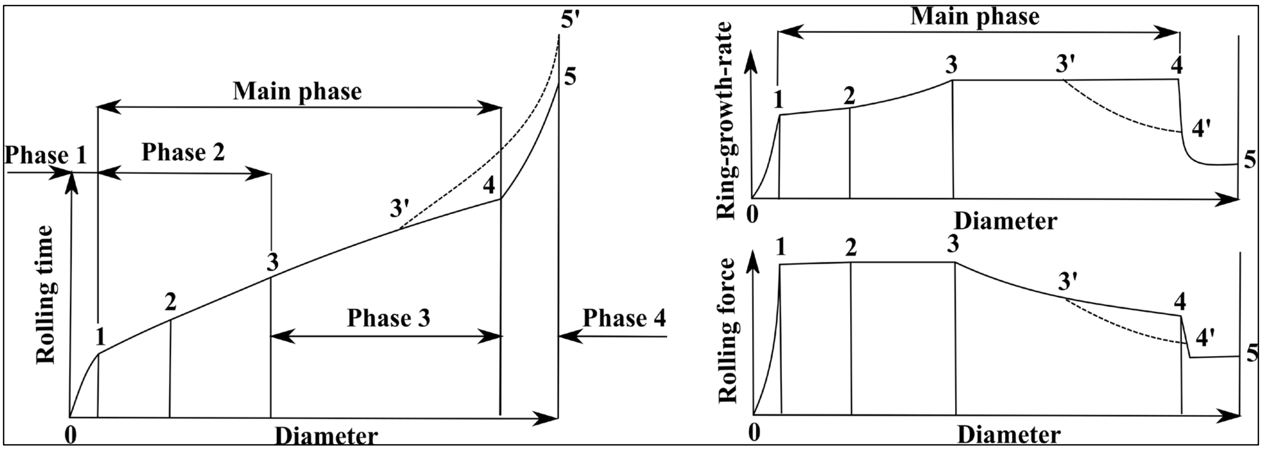

Figure 1: Representation of an idealized rolling phase of a RARR process adapted from [28]

3.2 Baseline ECTS approach

As a baseline the implementation of a non-myopic algorithm is adapted from [29,30]. The algorithm is non-myopic in the sense, that it calculates an optimal time to give a prediction for each time step. This algorithm is chosen as a baseline comparison as it uses a k-nearest-neighbor classifier and chooses the time steps at which a prediction is made automatically, depending on some hyper-parameter choices (used choices in brackets). One parameter was the cluster size (2) for a needed clustering within the model. The next was a lambda (15) value for the evaluation of a prediction during the computation of the cost function. The cost time parameter, alpha (0.0001), is used to shift the trade-off between earliness and accuracy. Lastly, the minimum length (15) for a prediction is set via a separate hyper-parameter. The MPL for the baseline approach needs to be investigated and is only influenced by the hyper-parameter choice.

3.3 Domain-specific rolling phase approach

The domain specific rolling approach has been briefly discussed earlier. The general idea is to predict ovality on-line at designated process states to ensure, that if a prediction is made that requires a process intervention, suitable counter methods can still be applied and the process is not too advanced. This is done even though the accuracy might suffer in order to reach hard earliness requirements. Counter methods such as a dislocation of the ring or an induced change in the axial frame force might not be established with measurable effects if the process is too advanced. This leads to the proposed approach to predict at the end of each rolling phase, depicted in Figure 1. Thus, the MPL for the domain specific approach is set to either one of the four phase endings.

3.4 Summary of chosen approaches

This baseline approach was chosen to investigate the different prediction times, depending on the aforementioned hyper-parameters, if they were chosen automatically. Whereas the domain specific prediction times of the domain specific approach are fixed with regard to each individual process. These prediction times will be investigated and discussed within the evaluation in the next section. It will be analysed whether the domain specific approach and the corresponding process phase endings show similar MPL or are completely different.

4. Experiments

The conducted experiments where divided into two parts. In the first part the automatically chosen prediction times using the baseline approach were investigated using model trainings on the train and test split. The second part uses a domain specific approach on the five-fold shuffle split validation using a Time Series Forest (100 estimators, criterion=entropy, max features=log2), InceptionTime (batch size=32, number filters=64, use_residual=True, use_bottleneck=True, depth=9, kernel size=64) and LSTM-FCN (LSTM=2, Filters=[64,128,64], Kernels=[8,5,3]) model as those models have been proven to be suitable for the time series classification task in the domain of RARR.

4.1 Baseline-Approach

The non-myopic model was used to generate different prediction times. The hyper-parameters were chosen using a grid search and the final parameters are mentioned in section 3.2. The model was trained on both the raw data set as well as on the standardized data set to see if prediction times could vary with respect to value changes due to standardization and the cost time parameter used to force an earlier or later prediction with an accuracy trade-off. It can be seen in Figure 2 that the standardization does change the prediction time for the non-myopic model significantly, as there is a shift from a heavily separated prediction split from either very early and very late prediction towards a more divided prediction, yet the high predictions at a very early stage of the process still occur in the standardized data.

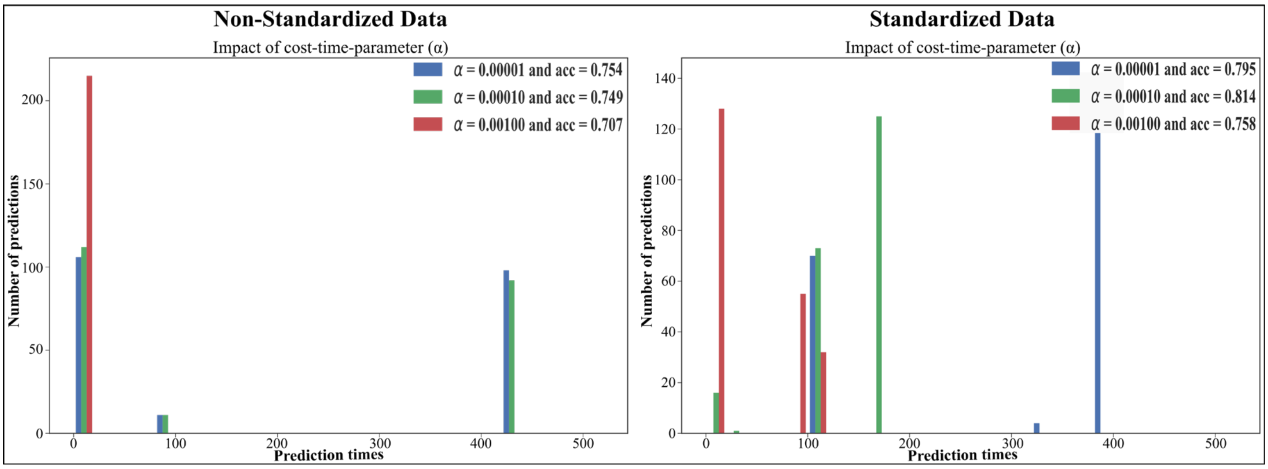

Figure 2: Differences in the earliness of predictions regarding standardization

Moreover, regarding the accuracy within both data sets, it can be seen that with a lower alpha value the accuracy is lower due to the bigger focus on earlier predictions. Yet, it is surprising, that the lowest alpha value does not always produce the highest accuracies, as for the standardized data set predictions with an alpha value of 0.0001 produce a higher accuracy even though the predictions were made earlier than those with alpha 0.00001. Further, Figure 3 depicts two samples (left and right) of the data set that are predicted using the different alpha models and showing the results regarding accuracy. In the example, it can be seen that the prediction made on the bottom (red line) prediction is incorrect for both samples as the time series could not be distinguished correctly by the model at this early stage. The blue (first) and green (second) lines predictions show the later predictions. In this example the latest prediction correctly classifies both example, whereas the second model using an alpha value of 0.0001 does only correctly classify one of the two examples.

Inspecting not only those two examples, it was hard to differentiate whether there is a specific point in the process to which extend all information needed was gathered by the non-myopic approach. Yet, the prediction switches towards the depicted times at about 180 time steps (green) and 390 (blue) seem similar to the process phase approach discussed in the next section.

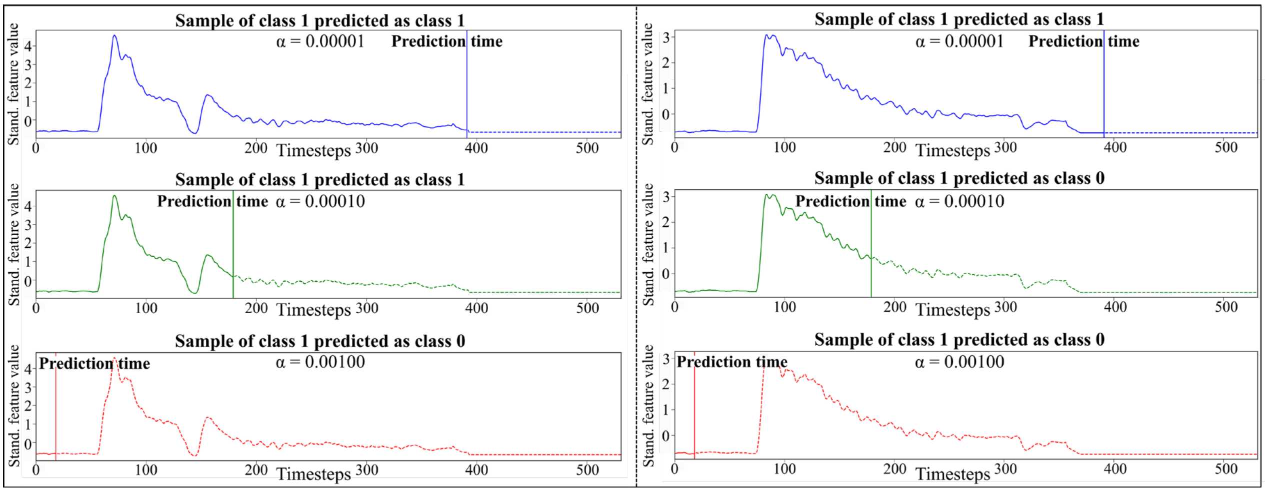

Figure 3: Visualization of different predictions on two samples made by the three different non-myopic models

4.2 Domain specific phase approach

The aforementioned similarity can be seen by analyzing the average phase lengths of each sample. Figure 4 shows the range of the phase lengths on the left side and the cumulated time steps each phase ends on the right. It can be seen that the ending of phase one at about ten time steps is similar to the very early predictions of the non-myopic model. The average phase ending of phase two on the right shows a direct similarity to the model depicted in green in Figure 2. Yet, the average phase ending of phase three at about 320 on the right of Figure 3 is slightly earlier than the prediction made in blue in Figure 2.

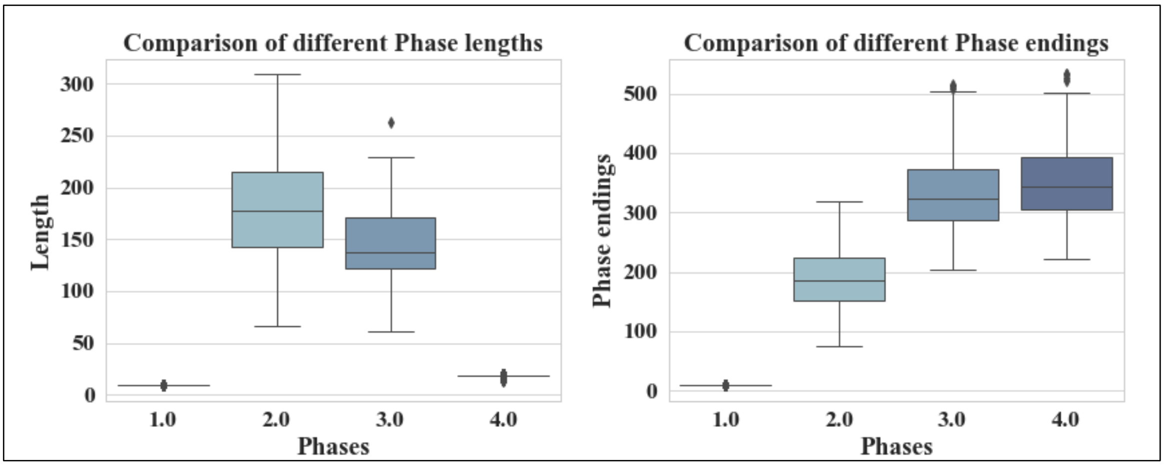

Figure 4: Comparison on the phase lengths and phase endings for the underlying RARR data set

Table 1 shows the test results of the five-fold shuffle split validation training with five runs each for the LSTM-FCN, Inception and Time Series Forest model. It can be seen that the accuracy drop between the predictions after phase one and two as well as phase two and three are noticeable yet between phase three and four are only minor. It is surprising, that the best mean (0.884) and maximum (0.921) accuracy for not standardized data reached for all phases was after phase three and not after phase four. Moreover, it can be seen, that the Time Series Forest performs very well overall and even best when looking at not standardized data in Table 1. For a very early prediction e.g. after phase two the LSTM-FCN Model is performing best.

With regard to the real-world deployment of those models it has to be discussed whether a prediction after phase two or three needs to be forced if the chosen counter measurements need to be applied during the earlier stages of the ring rolling process. The accuracy of the best performing models with regard to the phase is decently high, yet to be deployed into an industrial production chain the accuracies should improve to higher levels.

Table 1: Test-results for the early prediction using the domain specific rolling phase approach

Rolling Phase	No Standardization		Standardization		Classifier
	mean	max	mean	max	
1	0.762	0.805	0.762	0.800	Inception
	0.771	0.800	**0.772**	**0.805**	LSTM
	0.812	**0.847**	0.732	0.753	TSF
2	0.864	0.888	0.856	0.893	Inception
	0.866	**0.902**	**0.867**	**0.907**	LSTM
	0.863	0.888	0.845	0.888	TSF
3	0.868	0.898	0.866	0.898	Inception
	0.871	0.907	0.868	0.898	LSTM
	0.884	**0.921**	**0.878**	**0.907**	TSF
4	0.870	0.907	0.867	0.907	Inception
	0.868	0.907	0.873	**0.912**	LSTM
	0.882	**0.916**	**0.879**	0.907	TSF

5. Conclusion

Within the present research, after reviewing the state of the art for TSC and ECTS, the fundamentals of RARR were explained. Then, the dataset used was described and a baseline and domain-specific approach was presented. Within the experiment section, both approaches were analyzed and compared and achievable accuracies of the ECTS case were presented. The investigation of the different prediction times chosen by the non-myopic approach showed, that the prediction times occur roughly at the same time as the ring rolling process phase changes. This underlines the used approach to link the prediction of different models to the rolling phase changes as it is done in section 4.2. The overall better performance of the domain specific approach is due to the different and more complex models used and the baseline approach was used to gather useful information about the minimum prediction length of the data. For the implementation at the radial-axial ring rolling mill at the chair of production system real world experiments will be carried out using the early prediction models to initiate counter measurements to avoid ovality, resulting in better quality.

6. Future Work

The aforementioned results will be used to deploy an on-line system for quality prediction at a ring rolling mill. Depending on the different levels of earliness of the predictions different counter measurements will be triggered via a direct connection to the CNC: Further validations regarding those counter measurements will be conducted. Moreover, the earliness and accuracy will be constantly improved and the data set will be enlarged to achieve higher prediction accuracies throughout all rolling phases.

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Biography

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