Complementary database generation for machine learning in quality prediction of cold ring rolling

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Abstract

Reducing scrap products and unnecessary rework has always been a goal of the manufacturing industry. With the increasing data availability and the developments in the field of artificial intelligence (AI) for industrial applications, machine learning (ML) has been applied to radial-axial ring rolling (RARR) to predict product quality [1]. However, the accuracy of these predictions is currently still limited by the quantity and quality of the data [2]. In order to apply supervised learning to predict part quality and possible scrap parts, there must be plenty of datasets logged for both good and scrap parts. One suitable way to increase the number of datasets is to utilize simulation strategies to generate synthetic datasets. However, in the hot ring rolling field, there is no fast simulation method that can be used to generate a sufficiently large synthetic database of rolled parts with form or process errors. The research on transfer learning between different mills and datasets has offered a new idea of taking a cold ring rolling process as the object of study [2]. Next it will investigate the extent to which the cold ring rolling can be used as a similar process for future transfer of models and results to radial-axial ring rolling. Compared to RARR, the cold ring rolling is a process under room temperature and contains complete radial forming instead of simultaneous forming in the radial and axial directions. The simpler forming mechanism makes it possible to build a semi-analytical model, which takes much less time compared to conventional FEM-approaches under acceptable accuracies. Furthermore, the smaller ring geometry, simplified rolling process and reduced energy consumption mean that in-house experiments can be conducted to verify the quality of the synthetic data based on confidence intervals.

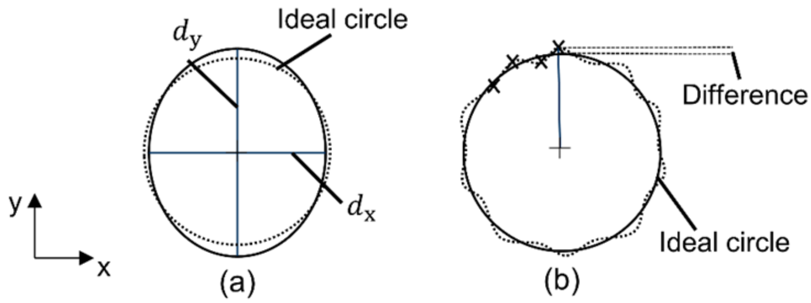

Figure 1: *Two types of non-circularity: (a) Ovality, (b) Irregular error*

In this study, three methods are used to generate a large amount of real and synthetic data: experiments, FEM and semi-analytical method. Experiments will be conducted based on a full three level and six factorial design with a total of 729 combinations. These six selected factorials are important parameters for the rolling process based on experience and can be easily adjusted in practice. For the experiments, there will be three repetitions, and for the simulation one repetition. The Design of Experiments (DoE) is aiming to create a database, where the ML-Algorithm obtains for all geometries the relevant parameter contributions with a sufficient amount of data points. A 3D full ring FE model is built, which corresponds as close as possible to real geometry and kinematics. It has 10k elements and is calculated for 250 CPU Hours using explicit solver in LSDYNA. Process parameters are automatically extracted using a python script and stored in an hdf5 file. These parameters are the features of the supervised learning model, with corresponding form errors as the labels. The considered approach is a time series classification (TSC) task, where the entire time series of one rolling process is assigned to the corresponding form error label. There are following three types of form errors considered: out-of-roundness, cross-section error and height deviation. To evaluate these form errors, the geometry of the final ring needs to be analyzed. For the simulation, a points cloud file will be exported for each final ring. An algorithm has been established for evaluating out-of-roundness. The final ideal diameter is determined, and then the deviation of the points cloud from the ideal circle is computed. A criterion should be set up to differentiate between good and scrap parts. There are different ways of evaluating the two types of non-circularity (see Figure 1), and the results are not the same. As to which calculation method should be chosen, it is necessary to investigate which kind of non-circularity dominates after obtaining the experimental results. For the other form errors, a similar approach will be taken to generate the labels for the supervised learning. As for the experiments, 3D measurements will finally be adopted to get the shape information of the ring. The evaluation criterion for the real rings needs to be consistent with that of the points cloud described above.

Keywords *Cold Ring Rolling, FEM, DoE, Form Errors, Database*

References

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