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Estimation of rolling process variation by usage of a Monte-Carlo method

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Abstract. Rolling simulation, especially for groove rolling, is heavily dominated by use of finite element methods, but simulating a full pass sequence often takes several hours. Simpler models offer high-speed simulation within seconds at the expense of resolution and accuracy. In mechanical engineering, Monte-Carlo approaches are well known for analysis of fabrication tolerances in component assembly. By usage of fast simulation cores, this technique becomes available for analysis of process variations in groove rolling, since computational costs are crucial due to the need of hundreds or thousands of simulation runs. Rolling process variations can be classified in two groups: first, variations of the input material, such as actual dimensions, temperature and microstructure state; second variations occurring during processing, such as transport times, environment temperature and tool wear. The regarded process was the operation of the experimental semi-continuous rolling plant at the Institute of Metal Forming (IMF). Simulations were carried out by use of the open source rolling framework PyRolL, developed at IMF. The main part of process parameters was considered as constant, but some were described as a statistical distribution. For each simulation run a set of actual sample values of the distributed parameters was drawn using a random number generator. Selected result values were described by use of statistical methods to analyze the variational behavior of the process in behalf of the two variation classes.

Introduction

The term Monte Carlo Method (MCM) generally refers to a class of methods, which are characterized by the use of random numbers. These methods are rather diverse and serve different purposes. Here, the term shall be used for the concept of drawing random numbers as input for a function and analysing the results of several evaluations of this function, with different random inputs, with statistical methods. A detailed overview on this type of Monte Carlo methods is given by Lemieux [1]. The nature of the function can be complex, even of a black-box type, where nothing about the internals of the function is known but the input and output interfaces. In this case, Monte Carlo methods can provide valuable information about the behavior of the function while altering inputs.

Here, the function equals the simulation procedure, so it is generally known, but complex. For example, it is generally not possible, to compute derivatives of the outputs in dependence on the inputs in an analytical way. Even numerical derivation is hard, due to the multi-dimensional nature of most natural or technical systems.

The use of Monte Carlo methods for the analysis of variations in technical processes was reported before in the field of assembly of complex structures, like in mechanical engineering and building construction (f.e. [2-7]). However, in the field of rolling processes, there was no such attempt yet to the knowledge of the authors. The authors have previously used a similar approach to model powder morphology influences in sintering processes [8, 9]. The current work shall show

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the possibility of the application of Monte Carlo methods for the analysis of process variations in rolling processes. The focus lies hereby on the estimation of the workpiece temperature evolution. The temperature evolution is crucial for the microstructure development of the workpiece, which shall be investigated in a following work. The influence of variations in the initial workpiece and within the regarded process route is analysed and evaluated. Due to the need of a large number of function evaluations (simulation runs), the evaluation speed of the process model is crucial to the applicability of this approach.

Rolling simulation is currently dominated by the use of finite element (FE) based models. These are offering high accuracy and high resolution results at the expense of high computational resource usage. So, these methods are inconvenient for the current need. Therefore, one-dimensional approaches shall be used here. These offer less accuracy and limited resolution, but are computable within fractions of seconds on typical personal computer systems. The current work is based on the open-source rolling simulation framework PyRolL [10], developed by the authors, which is a fast, open and flexible software package mainly aimed at groove rolling in reduction passes. The models used for the different parts of the problem can be exchanged and extended with low effort to the user's needs.

Method

The Institute of Metal Forming operates a semi-continuous pilot rolling plant, which is the object of the current investigation. It consists of a two-high reversing roughing stand and four continuous finishing stands. The pass schedule of the current work consists of 10 oval-round reversing passes followed by 4 oval-round continuous finishing passes. A 50 mm round workpiece made of a mild structural steel is rolled down to 8 mm diameter. Details of the schedule are provided in the supplemental material [11], as the exact properties of the pass schedule are of minor importance for the statements of this work.

Monte Carlo Approach.

The basic idea of the approach shown here is to simulate the rolling process several times with different input values, which are drawn by a random number generator according to predefined statistical distributions. Afterwards, the distribution of the results can be analysed by classic methods of descriptive statistics to obtain information about the process' variational behavior. The principle is shown in Fig. 1.

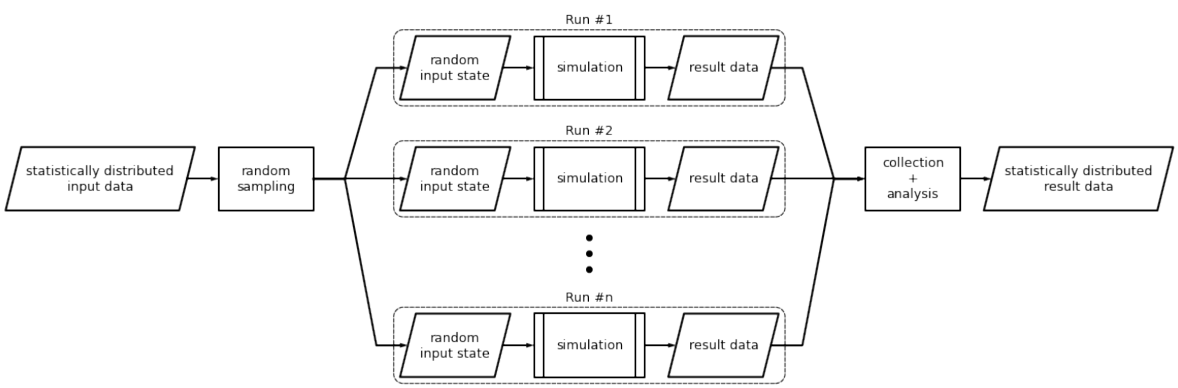

Fig. 1. Chart of the Concept of Variation Estimation Using Monte Carlo Techniques.

This approach provides information about the overall variational behavior of the process. If a single source of variation is introduced in the input, the reaction of the process on this variable can be analysed. The count of variation sources introduced is generally unbounded. The tracing back of result variations to the input can be done using classic correlation methods of descriptive statistics, however, with the same typical caveats. The main benefit of the approach is, that no information about the internals of the simulation procedure is needed for variational analysis,

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especially there is no need for derivatives of result values in dependence on the input. The simulation procedure can generally be treated as black box with defined input and output interfaces.

The key problem is to obtain data describing the variations of the input variables. In this work two showcases shall be regarded: first the variation of the initial workpiece in diameter and temperature, second the variation of the inter-pass durations between the reversing passes. This choice was taken, since two fundamentally different types of variation sources were suspected. First, sources in the initial workpiece, which are applied only once, but traverse the whole process line. Second, variations in the process itself, which affect the workpiece state in each process step anew.

The question of varying inter-pass durations is crucial for scientific experiments on microstructure evolution, but currently often neglected. Mostly, only flat durations between the reversing passes are included in the design calculations. Due to manual transport and feed of the workpiece to the following roll pass, the scheduled inter-pass durations are never realized in practice. Although, these deviations from the schedule influence the microstructure evolution of the sample, as well as the actual conditions in the roll passes. The current approach is aimed to help quantifying these deviations.

Data Acquisition.

The pilot plant at IMF is equipped with several measurement and data collection systems. Data from a number of rolling trials have been collected and analysed to obtain the inter-pass durations t between the reversing passes. The complete dataset and analysis routines are available in the supplemental material [11].

For the approximative description of the durations' distribution, a gamma distribution was used, which is a generalized exponential distribution. The probability density function (PDF) of the gamma distribution is defined as in Equation 1, where Γ is the gamma function and $\alpha > 0$ and $\beta > 0$ are parameters.

$$f(x) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} \exp(-\beta x) \quad (1)$$

Since the gamma distribution is only defined for $x > 0$, but no inter-pass durations below a certain value occur due to technical restrictions, the distribution was modified by introducing a minimal inter-pass duration t_0 with $x = t - t_0$. So, there are three free parameters α, β and t_0 for fitting of the distribution function. The fitting was done using least squares optimization of the resulting PDF function on the density histogram of the data. Statistical analysis and model fitting were done by use of the SciPy [12] and Pandas [13, 14] software packages.

Core Simulation Procedure.

In the current work, the open-source rolling simulation framework PyRolL [10] was used to simulate the rolling process. Generally, the shown approach can be used with every rolling simulation software available, since the procedure does not depend on any internals of the simulation. A fast simulation approach, however, is favourable, since the simulation has to be done several, up to hundreds of, times. The models used here are of one-dimensional type, thus, they lack of resolution in other directions as the rolling direction and provide only limited accuracy, but at the benefit of high solution speed. They typically combine empirical approaches with simplified analytical solutions. PyRolL is designed to offer simple exchangeability of the used model approaches. The model set can be chosen in a modular way by loading plugin packages. The current simulation was done with the basic configuration of PyRolL, which includes the empirical roll force and torque model of Hensel and Spittel [15], an integral thermal model approach according to Hensel et al. [16], contact area estimation according to Zouhar [16] and roll flattening according to Hitchcock and Trinks [18]. Spreading was simulated using the equivalent flat pass according to Lendl [19-21] in conjunction with the spreading equation of Wusatowski [22]. The calculation time of one simulation run is below 1 s on typical current desktop computer systems. Details of software construction and model equations are provided in the documentation of PyRolL [10].

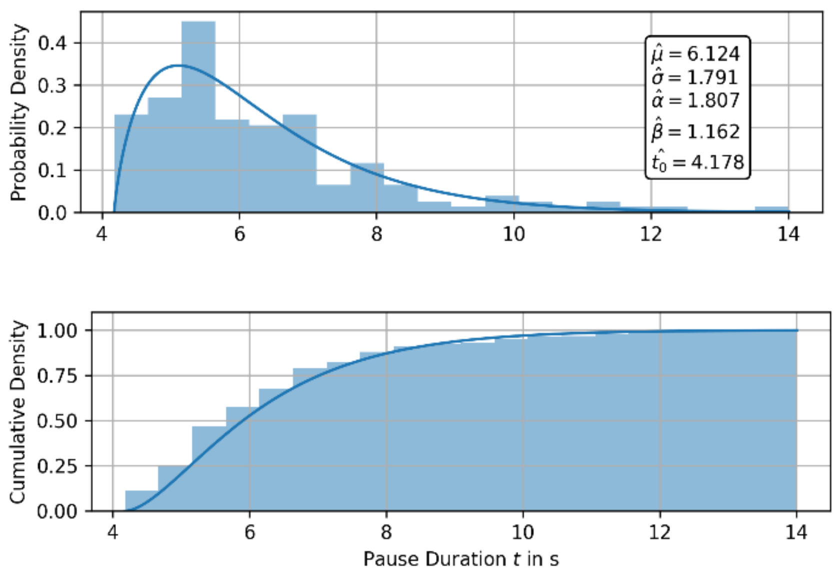

Fig. 2. Histograms of Inter-Pass Duration Between Roll Passes of the Reversing Mill.

Results

Inter-pass Durations For the analysis of the inter-pass durations a set of 29 rolling trials was analysed. The histograms of the obtained dataset are shown in Fig. 2 in conjunction with the fitted distribution parameters. The mean inter-pass duration was about $\mu(t) = 6.1$ s. The 90 % confidence interval is between 4.50 s and 9.32 s. Data points larger than 15 s were capped as outliers, since they occurred very rarely and are related to operational problems.

Simulation Showcases.

In the following, two showcases of the Monte Carlo approach described above shall be shown. For each case 100 sample conditions were drawn using a random number generator. The current analysis was limited to the aspect of temperature evolution as example for the possibilities of the method, although other key problems such as roll force and torque, spreading and filling, as well as elastic rolling stand behavior are included in the simulation core. The temperature evolution was selected, because it is the most vivid property of the process to show the importance of variation analysis. It influences directly and substantially the plastic material behavior and the evolution of the microstructure, while it is quite sensitive to most process conditions. More detailed data is included in the supplemental material [11].

The first showcase is the analysis of variations solely in the input workpiece. Exemplary, the diameter d of the round profile and the mean initial temperature T of the workpiece were chosen. Their variations were modelled using normal distributions with the nominal values as mean $\mu(d) = 50.0$ mm resp. $\mu(T) = 1373$ K and standard deviations of $\sigma(d) = 1.0$ mm resp. $\sigma(T) = 10$ K. The inter-pass durations were here chosen as an approximate constant of $t = 6.1$ s (corresponding to the mean inter-pass duration above) for the reversing passes, but were calculated directly from rolling velocity and distance for the continuous passes.

The resulting temperature evolution is shown in Fig. 3. The variations of the incoming and outgoing temperatures at each roll pass are plotted as boxplots in the respective positions. Two

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line plots show the results of the simulation using only the nominal values and the mean curve of the Monte Carlo results. These were rather equivalent in this case. The variations of the simulation results tended to decrease along the pass schedule, compare also Fig. 5. In the continuous passes, the variations of the workpiece temperatures were rarely significant. This is in accordance to practical experience.

The second showcase is the consideration of the varying inter-pass durations during operation of the reversing mill due to manual feeding. The durations were drawn from the gamma distribution created above. The remaining parameters were the same as in the first case.

The resulting temperature distribution is shown in Fig. 4 similarly to the first case. The standard deviations of both cases are compared in Fig. 5. In contrast to the first case, the variations of the workpiece temperature are not decreasing along the pass schedule but in the finishing passes, since additional variation is introduced between each pass of the reversing mill. So the variation of the utput workpiece is higher than that of the input. Additionally, the mean of the Monte Carlo results tends to deviate from the nominal results, unlike the first case.

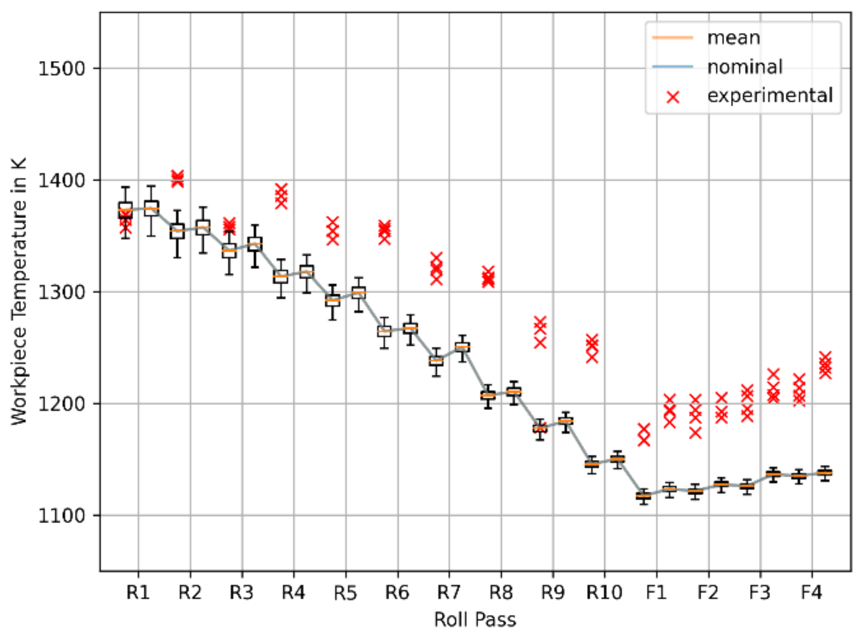

Fig. 3. Temperature Evolution Within the Rolling Process Under Variation of the Initial Workpiece.

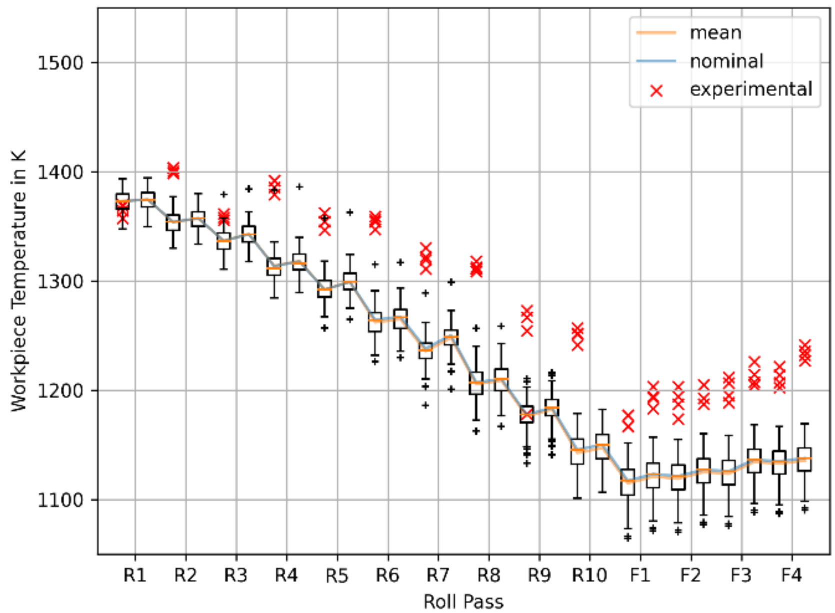

Fig. 4 Temperature Evolution Within the Rolling Process Under Variation of the Initial Workpiece and of the Inter-Pass Durations.

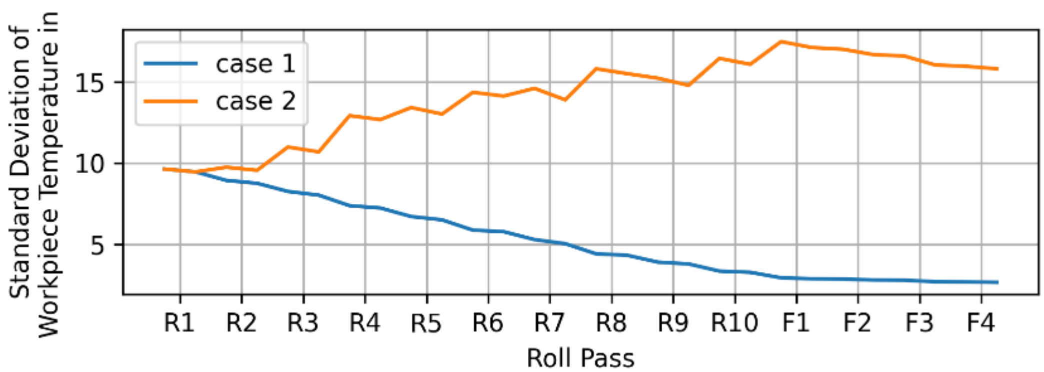

Fig. 3. Evolution of the Temperature Standard Deviation.

Summary

The current work showed the general applicability of Monte Carlo method based variation estimation techniques on the variational behavior of rolling processes. Two different kinds of variation sources in rolling processes were identified: first, variations in the input workpiece, second, variations within the process. They showed fundamentally different behavior. While variations in the input workpiece tend to vanish along the process, variations in the process itself accumulate and lead to high variations in the product. This leads to the conclusion, that the control of variations within the process is crucial in comparison to variations in the input material.

Especially in the case of manual feeding of a reversing mill, as common in pilot plants, this has to be kept in mind. It can be stated, that a well-controlled process should tend to decrease the variations of its input workpiece. These findings are in accordance to practical experience. In following work, the concept will be extended by the use of more advanced models within the simulation core. However, this has to be done always with the computational effort in mind, since the core simulation must be carried out up to hundreds of times. With the use of locally resolved models, estimations regarding the variation of local workpiece state can be carried out. Especially in terms of microstructure evolution, this would be a valuable contribution to the interpretation of experimental results. In the future, this approach can help to identify sources of variations within a process and evaluate their influence on the resulting output variations.

A key is the acquisition of a statistical description of the process parameters. A first estimate can be given by a normal distribution with a certain standard variation around the nominal parameter value. For more accurate results, the collection of data in the running process may be appropriate, as was shown for the inter-pass durations. The method's reliability is dependent on both, the accuracy of the simulation models and the statistical parameter description.

References

[1] C. Lemieux, Monte Carlo and Quasi-Monte Carlo Sampling, Springer New York, (2009). ISBN: 978-0-387-78165-5. https://doi.org/10.1007/978-0-387-78165-5.

[2] C.-Y. Lin, W.-H. Huang, M.-C. Jeng, J.-L. Doong, Study of an Assembly Tolerance Allocation Model Based on Monte Carlo Simulation, J. Mater. Process. Technol. 70 (1997) 9-16. https://doi.org/10.1016/S0924-0136(97)00034-4.

[3] Zhengshu Shen, Gaurav Ameta, J.J. Shah, J.K. Davidson, A Comparative Study Of Tolerance Analysis Methods, J. Comput. Inform. Sci. Eng. 5 (2005) 247-256. https://doi.org/10.1115/1.1979509.

[4] J.-Y. Dantan, A.-J. Qureshi, Worst-Case and Statistical Tolerance Analysis Based on Quantified Constraint Satisfaction Problems and Monte Carlo Simulation, Computer-Aided Design 41 (2009) 1-12. https://doi.org/10.1016/j.cad.2008.11.003.

[5] A.-J. Qureshi, J.-Y. Dantan, V. Sabri, P. Beaucaire, N. Gayton, A Statistical Tolerance Analysis Approach for Over-Constrained Mechanism Based on Optimization and Monte Carlo Simulation, Computer-Aided Design 44 (2012) 132-142. https://doi.org/10.1016/j.cad. 2011.10.004.

[6] H. Yan, X. Wu, J. Yang, Application of Monte Carlo Method in Tolerance Analysis, Procedia CIRP. 13th CIRP Conference on Computer Aided Tolerancing 27 (2015) 281-285. https://doi.org/10.1016/j.procir.2015.04.079.

[7] C. Rausch, M. Nahangi, C. Haas, W. Liang, Monte Carlo Simulation for Tolerance Analysis in Prefabrication and Offsite Construction, Automat. Constr. 103 (2019) 300-314. https://doi.org/10.1016/j.autcon.2019.03.026.

[8] M. Weiner, M. Schmidtchen, U. Prahl, A New Approach for Sintering Simulation of Irregularly Shaped Powder Particles - Part I: Model Development and Case Studies, Adv. Eng. Mater. 24 (2022). https://doi.org/10.1002/adem.202101513.

[9] M. Weiner, T. Zienert, M. Schmidtchen, J. Hubálková, C.G. Aneziris, U. Prahl, A New Approach for Sintering Simulation of Irregularly Shaped Powder Particles - Part II: Statistical Powder Modelling, Adv. Eng. Mater. (2022) 202200443. https://doi.org/10.1002/adem.202200443.

[10] M. Weiner, C. Renzing, M. Stirl, and M. Schmidtchen. PyRolL. Version 1.0.5. Institute of Metal Forming, TU Bergakademie Freiberg. URL: https://pyroll-project.github.io.

[11] M. Weiner, C. Renzing, R. Pfeifer, M. Schmidtchen, U. Prahl. Supplemental Material to 'Estimation of Rolling Process Variation by Usage of a Monte-Carlo Method' at ESAFORM2023. 2022. https://doi.org/10.25532/OPARA-195.

[12] P. Virtanen, R. Gommers, T.E. Oliphant, M. Haberland, T. Reddy, D. Cournapeau, E. Burovski, P. Peterson, W. Weckesser, J. Bright, S.J. van der Walt, M. Brett, J. Wilson, K. Jarrod Millman, N. Mayorov, A.R.J. Nelson, E. Jones, R. Kern, E. Larson, C.J. Carey, I. Polat, Y. Feng, E. W. Moore, J. VanderPlas, D. Laxalde, J. Perktold, R. Cimrman, I. Henriksen, E.A. Quintero, C.R. Harris, A.M. Archibald, A.H. Ribeiro, F. Pedregosa, P. van Mulbregt, SciPy 1.0 Contributors, SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python, Nat. Methods 17 (2020) 261-272. https://doi.org/10.1038/s41592-019-0686-2

[13] pandas-dev/pandas: Pandas (2020). https://doi.org/10.5281/zenodo.3509134

[14] W. McKinney, Data Structures for Statistical Computing in Python, Proceedings of the 9th Python in Science Conference (2010), pp. 56-61. https://doi.org/10.25080/Majora-92bf1922-00a
[15] A. Hensel, T. Spittel. Kraft- und Arbeitsbedarf bildsamer Formgebungsverfahren, VEB Deutscher Verlag für Grundstoffindustrie, 1978.
[16] A. Hensel, P. Poluchin, W. Poluchin, Technologie der Metallformung. Deutscher Verlag für Grundstoffindustrie, 1990.
[17] G. Zouhar, Umformungskräfte beim Walzen in Streckkaliberreihen, Akademie Verlag Berlin, 1960.
[18] J. H. Hitchcock, W. Trinks, Roll Neck Bearings. Report of Special Research Committee on Roll Neck Bearings, ASME (1935) 51.
[19] A. E. Lendl, Rolled Bars - Part I - Calculation of Spread between Non Parallel Roll Surfaces, Iron and Steel 21.14 (1948) 397-402.
[20] A. E. Lendl, Rolled Bars - Part II - Application of Spread Calculation to Pass Design, Iron and Steel 21 (1948) 601-604.
[21] A. E. Lendl, Rolled Bars - Part III - Application of Spread Calculation to Diamond Passes, Iron and Steel 22 (1949) 499-501.
[22] Z. Wusatowski, Fundamentals of Rolling, Pergamon Press, 1969.