Monitoring of fluctuating material properties for optimizing sheet-metal forming processes: a systematic literature review

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Abstract. Material properties can vary both along a sheet-metal coil and from coil to coil despite tight tolerances influencing the process stability of sheet-metal processes and the part quality, which leads to rejects and machine downtime [1]. This significantly affect the economic efficiency of the process. Monitoring fluctuations in material characteristics at regular intervals along sheet-metal coils is enabled directly by non-destructive testing (NDT) before the process offering conclusions on the material properties. Another material monitoring technique arises from monitoring process conditions of the upstream processes, e.g., cold rolling, leading indirectly to insights on material properties. In this work, a systematic literature review (SLR) [2] is conducted to investigate recent approaches for material monitoring and for the utilization of resulting material data for optimizing different sheet-metal forming processes. Existing approaches for different sheet-metal forming processes are critically appraised. Based on the SLR research gaps are revealed and research opportunities, e.g., arising from a potential transfer of existing solutions between different forming processes and recent advances in data-driven methods, are identified.

Introduction

Despite tight tolerances, variations in material properties along a sheet-metal coil or between different batches of the same material have been shown to occur during sheet-metal production [3]. These material fluctuations lead to defects such as burr formation or dishing behavior in shearing processes and to defects such as spring back in bending or forming operations [4]. Thus, fluctuating material properties result in rejects, robustness problems and downtime of sheet-metal forming processes. Typically, material properties are only measured at the beginning and at the end of coils. This makes it difficult to draw conclusions about the material quality in the event of defects.

With the rise of the digital transformation in manufacturing to the Industry 4.0 the concept of the Internet of Production is gaining more importance [5]. In an Internet of Production all process-characterizing information about a production process is available for the realization of real-time process control and decision support. In the case of material variation that means the information about the material properties along the coil needs to be available to achieve full transparency, to adapt the process to changes in material properties and in case of workpiece defects to provide data for effective troubleshooting.

One solution to this problem is to measure or monitor the material characteristics along the sheet-metal coil before the sheet-metal process with the help of non-destructive testing (NDT). Already in 1994, Engel et al. demonstrated the potentials of NDT for sheet-metal processes [6]. Nowadays NDT allows drawing direct conclusions about material properties, such as tensile strength or elongation at break, and can be performed inline at regular intervals along the coil as it is being processed [7].

Besides NDT, another approach to material monitoring arises from monitoring process conditions of the upstream processes of sheet-metal forming processes, e.g., hot rolling [8], leading indirectly to insights on material properties. The use of cross-process data fundamentally enables the identification of quality-relevant parameters in the process chain and thus, the optimization of the process itself or of the subsequent process in the process chain. The sharing of information along the process chain is one of the main goals of an Internet of Production.

Since a lot of research is already done in this field, this paper methodologically researches the approaches to handle fluctuating material properties for the usage in an Internet of Production. The two presented approaches of monitoring material properties along sheet-metal coils lead to following research questions:

RQ1. How can fluctuating material properties be directly measured by NDT?
RQ2. How can fluctuating material properties be indirectly measured by monitoring the upstream process?
RQ3. How is the knowledge of fluctuating material properties along the coil utilized to optimize sheet-metal processes?

To answer these questions a systematic literature review (SLR) is conducted. First, the research methodology is described in section 2 and after that in section 3,4 and 5 the research questions are discussed chronological based on the results of the SLR. In section 6, research gaps in the field of material monitoring are identified.

Research Methodology

The research methodology of the conducted SLR is based on the research methodology from Xiao and Watson [2]. It consists of three stages planning, conducting and reporting with different steps (Fig 1). The problem formulation is already described in section 1 in the form of three research questions.

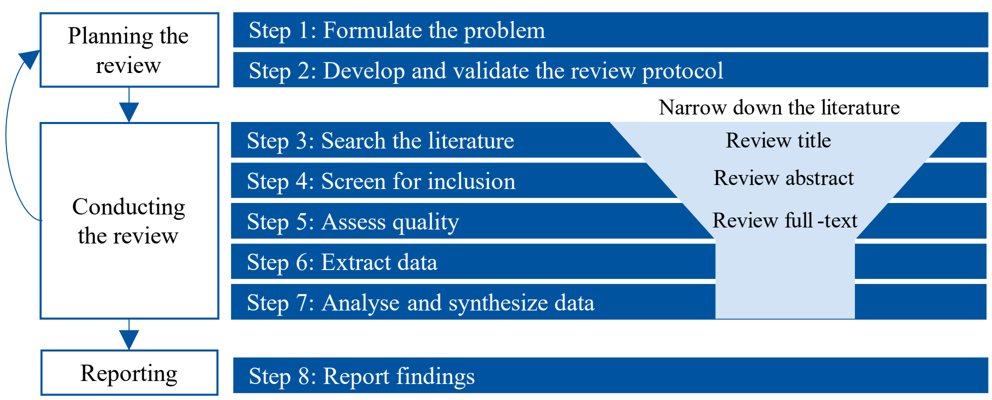

Fig. 1. Methodology of the SLR (adapted from [2]).

Based on these research questions, topics for keywords were selected (see Table 1). The first keyword topic focusses on “mechanical properties” and “material variations” ensuring that the retrieved literature contains these or synonyms of these terms. In addition, the literature search is intentionally limited to publications on sheet-metal forming, in particular, common sheet-metal forming or shearing technologies and the most important upstream processes for the production of sheet-metal coils. Here common sheet-metal forming processes were chosen. The last keyword topic focuses on different monitoring and utilization methods of known material properties based on the fact that known material characteristics are used for control or data-driven analysis.

Table 1. Keywords of the conducted SLR.

Material Properties		Sheet Metal Forming		Processes		Utilization
material variation **OR** material fluctuations **OR** material variability **OR** material scatter **OR** mechanical properties **OR** material properties **OR** steel strip properties **OR** sheet metal properties **OR** material characteristics **OR** material measurements	**AND**	sheet metal forming **OR** metal forming **OR** forming technology **OR** sheet metal separation **OR** strip steel **OR** steel sheets **OR** sheet metal **OR** sheet material **OR** steel strip **OR** cold rolled strip **OR** coil	**AND**	normal cutting **OR** shear cutting **OR** shearing **OR** blanking **OR** punching **OR** fine blanking **OR** fineblanking **OR**	**AND**	optimization **OR** monitoring **OR** NDE **OR** NDT **OR** non-destructive testing **OR** non-destructive evaluation **OR** non-destructive examination **OR** nondestructive testing **OR** nondestructive evaluation **OR** nondestructive examination **OR** eddy current **OR**
				stamping **OR** deep drawing **OR** car body part **OR** bending **OR**		closed loop control **OR** control materials **OR** feedback control **OR** feedforward control **OR** online control **OR** offline control **OR**
				levelling **OR** roller levelling **OR** roller leveler **OR** cold rolling **OR** hot rolling		machine learning **OR** AI **OR** digital transformation **OR** digital twin **OR** digitization **OR** digitalisation **OR** data based **OR** data driven **OR** decision support

With these keywords 355 publications were found in the database Scopus. Scopus only considers peer-reviewed papers, books, and conference papers. Duplicates and publications that were not in English or older than from the year 2000 were removed. Based on the research questions the publications were examined by their title and abstract. Then a backward/forward search was conducted. An overview of the conducted SLR is given in Fig. 2.

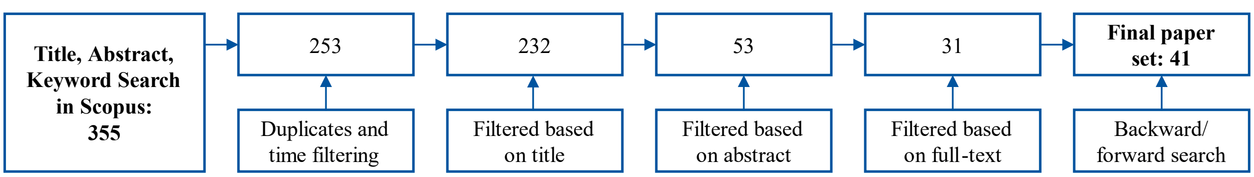

Fig. 2. Review process of the conducted SLR.

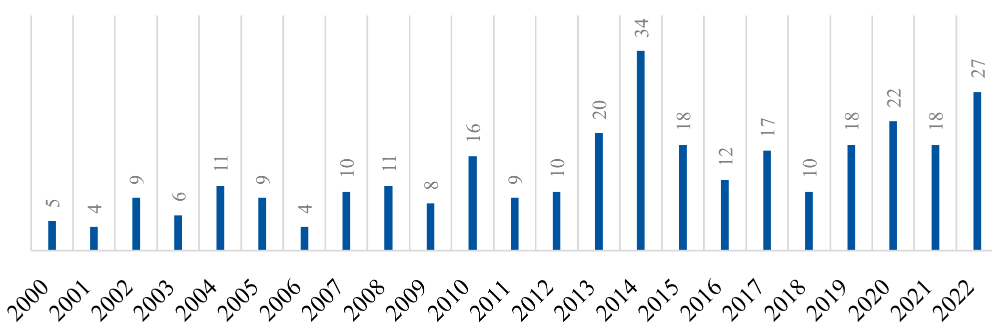

Fig. 3. Publication per year.

A first analysis of the publications per year shows that the topic of monitoring fluctuating material properties for optimizing sheet-metal forming processes became increasingly important until 2014 and after 2014 the importance remained, leading to the assumption that this topic is still relevant and will be relevant in the future.

To give a first overview of the results, Fig. 4 shows the number of publications found in the SLR after filtering for duplicates and time for different keyword topics displayed in the rows of column 3 of Table 1. It is evident that the topic of material variation is addressed primarily for the upstream processes, hot rolling, cold rolling, and roller levelling and for the sheet-metal forming processes stamping, deep drawing and bending. There are not many publications regarding sheet-metal separation processes.

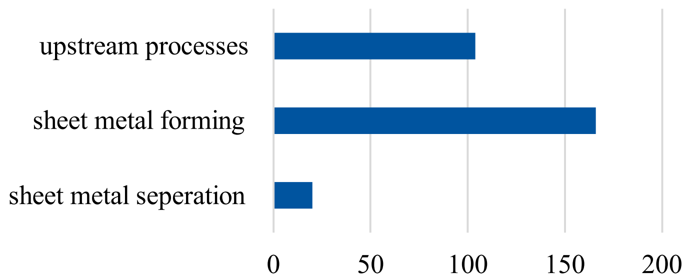

Fig. 4. Publication regarding different processes.

In the following three sections the research questions will be discussed based on the outcome of the SLR. A summary of the cited publications is given in Table 2.

Non-Destructive Testing in Sheet-Metal Forming (RQ1)

Non-destructive testing methods are suitable for measuring the material properties at regular intervals along the coil before the sheet-metal forming process. The operating principles of non-destructive testing methods include ultrasonic testing, X-ray examinations and electromagnetic methods. In sheet-metal forming, electromagnetic methods are commonly used because there is a correlation between the mechanical and electromagnetic properties of sheet-metal since the microstructure is influencing both. Several scientific publications study how signals from various electromagnetic sensors correlate with material properties.

For instance, Magnetic Barkhausen noise was used to measure hot-stamped high strength steel [9] and cold-rolled steel strips [10,11] in a lab setting. These measurements were used to predict different material properties, e.g., yield strength. Unterberg et al. distinguish whether material specimen were extracted from the start, the middle, or the end of a sheet-metal coil using a machine learning algorithm with magnetic Barkhausen noise as input data [12]. However, magnetic Barkhausen noise has not yet been used for inline monitoring.

Commonly used sensors for in-line measurements of sheet-metal material include, eddy current sensors (eddy current method), the 3MA sensor (micromagnetic, multiparametric microstructure and stress analysis), and the IMPOC sensor (magnetic inductive method). For each of these sensors, it has been shown that the sensor signals are related to the mechanical properties. Various publications report successfully using 3MA sensor for inline sheet-metal monitoring and predicting tensile strength, yield strength, residual stress, and hardness of the material along a coil with a regression based on 3MA data [13-15]. Heingärtner used multidimensional regression based on eddy current data to calculate the material parameters tensile strength, yield strength, uniform strain, and elongation at break in inline production [7]. Moreover, Lee et al. tested different machine learning algorithms to predict the yield stress and the uniform elongation based on 6 features of eddy current signals and achieved a high accuracy [16]. Zoesch et al. were able to detect cracks and thinning of material during deep drawing with two sensors (eddy current, 3MA) [17]. The IMPOC sensor was used to predict mechanical parameters such as tensile strength and yield strength [18] as well as to find uniformity in material properties along coils [19].

Indirect Measurements of Material Properties (RQ2)

The monitoring of processes that produce sheet-metal represents an alternative strategy to directly measuring the material in sheet-metal forming processes. The inline monitoring of sheet-metal producing processes not only facilitates the optimization of these processes itself, but also of downstream sheet-metal forming processes.

Table 2. Summary of the publication conducted in the SLR.

Research Question	Processes/Sensors	Literature
Fluctuating material properties	Sheet-metal forming in general	[1,3,4,20]
RQ1	Magnetic barkhausen noise	[9-12]
	Eddy current	[6,7,16,17]
	3MA	[13-15]
	IMPOC	[18,19]
RQ2	Hot rolling	[8,21-23]
	Cold rolling	[24]
	Roller levelling	[25-27]
	Stamping	[28]
RQ3	Stamping	[29-31]
	Deep drawing	[32-40]
	Bending	[41-43]

For the process of hot rolling, it was already shown in 2005 that it is possible to predict different mechanical properties such as yield strength of hot rolled steel coils based on data including process data such as coiling temperature and chemical factors with an artificial neural network. However, approximately 21% of the predicted yield strength values deviated more than ±15 MPA from the true value [23]. Chen and Fan showed in 2021 that based on the input data rolling temperature, curling temperature and the chemical composition of the material the material properties tensile strength, compression and elongation can be predicted by different regression models with an coefficient of determination of over 99% [8]. In [21] similar results were presented. In addition, electromagnetic monitoring was used in a hot strip mill to monitor the phase transformation and to extract the data of austenite transformation. Based on this data the hot rolling process was optimized in an offline control system [22]. Cuznar and Glavan investigated the data-driven optimization of the cold rolling process. The developed models enabled optimal cold rolling parametrization and real-time monitoring [24].

The roller levelling process was monitored by Nikula and Leiviskä using acceleration measurements. They utilized these measurements to predict the properties yield strength, width and thickness of the processed steel along the coil [27]. Magro et al. investigated an approach to predict the yield stress after the tension levelling process and to adapt the initial process parameters according to an analytical model [26]. Grüber and Hirt proposed a semi-analytical model that calculates the levelling force and determines in an inverse approach the material data [25].

In another approach, times series signals from force sensors of the stamping process as an upstream process are evaluated and used to predict the tensile strength, yield strength and elongation at break of the processed material [28].

Utilization of the Knowledge of Fluctuating Material Properties (RQ3)

Fluctuating material properties create uncertainties for downstream sheet-metal forming processes. These uncertainties influence the process stability, the process outcome and hence the product properties [20]. Thus, material fluctuations must be included in the process parameterization to increase the stability of the process or when adapting the process with different control strategies to optimize the process outcome.

For a stamping process, variations of material were measured with non-destructive testing and different motions for a servo-press were evaluated [29]. The data of this experiments were then evaluated using Bayesian logistic regression resulting in a model that determines motion profiles for a servo-press based on material characteristics [31]. Maretta and Di Lorenzo proposed a method were meta-models and Monte Carlo simulation were combined to analyze the influence of coil-to-coil material variations on thinning and spring back to enhance the robustness of a stamping process [30].

A method for knowledge-based control of a deep drawing process was proposed by Fischer et al., combining feedforward control based on inline material measurements from an eddy current sensor and feedback control based on inline measurements of draw-in [36]. Another approach to minimize the influence of material variation by feedback control was presented by the same author [37]. Heingärtner et al. implemented an intelligent control system using numeric simulations and material data acquired by eddy current, process settings and draw-in measurements to optimize the manufacturing of kitchen sinks and tested it on a production site [38].

Endelt distinguishes between non-repetitive uncertainties and repetitive uncertainties in sheet-metal forming. While non-repetitive uncertainties are for example variance in sheet thickness and uneven lubrication. The repetitive uncertainties are for example changes in material properties, tool wear and tool temperature, which lead to process downtimes [33]. To handle these uncertainties Endelt and Danckert proposed a control strategy with an inner loop reducing the current draw-in error of the produced part and an outer loop based on a iterative learning control scheme handling the repetitive uncertainties and transfer information to optimize the draw-in flange from the produced part to the next part [35]. Endelt tested also a similar approach of iterative learning control algorithms on two benchmark problems [34]. Furthermore, Endelt develop the control strategy based on an inner loop and an outer loop further by adding numerical simulations to reduce the draw-in error [33]. A numerical study for a deep drawing process, where material fluctuations were included through a sensitivity analysis, and a proof of concept for a new control strategy by adapting the blank position was conducted by Briesenick et al. [32].

Based on various material data such as IMPOC signals and oil levels recorded in a stamping plant, van Stein implemented an anomaly detection algorithm in a car body stamping process to detect outliers in material properties along steel coils [39]. On the same press shop, Purr examined various data sources in a press shop from various measuring systems also IMPOC signals with the aim of detecting fluctuations in the process. The result shows that the material fluctuations have a strong influence on the quality of the car body components [40].

In bending, material variations lead to spring back and thus, control strategies have been developed. A summary of these strategies is given in [20]. In this systematic literature review the focus was on the fluctuations of material properties. In [41] the authors used finite element simulation to identify a spring back compensation strategy. It was shown that this compensation strategy is able to reduce spring back under varying material properties and sheet thickness. Lafon et al. modelled different uncertainties, especially material properties to find a robust optimization procedure for a draw bending process [42]. The effect of yield strength variation and part dislocation was studied by Waheed et al. to optimize bending force and residual stresses [43]. It was found that the yield strength has a major effect on bending force and residual stresses.

Identified Research Gaps

The SLR revealed existing scientific studies, which already apply different NDT methods to obtain insights about material properties at regular intervals along sheet-metal coils in-line at the shop floor. Nevertheless, only few studies investigate in-line monitoring of material properties in relation to the parametrization of sheet-metal forming processes and the outcoming part quality at industrial scale. The investigation of non-destructive material measurements along coils offers the quantification of influences originating from the material and enables profound data-driven evaluation based on a high amount of available data to realize decision support and real-time control. Furthermore, NDT has been used to predict material properties by using features of raw signals but further investigation of correlations between specific signal properties of the raw signals and specific material properties provide an opportunity to derive new insights into potentially underlying cause-and-effect relationships.

Although existing publications already report that knowledge of material properties was obtained by monitoring upstream processes, in particular hot rolling, cold rolling, roller levelling and stamping, it is at best used to optimize the same process but there is no publication using these insights to optimize the subsequent sheet-metal forming processes. Compared to NDT, the approach to monitoring upstream processes usually requires cross-company collaboration, which, combined with the heterogeneity of the different process data, further complicates this approach. However, research on other manufacturing technologies suggests, that a holistic optimization of process sequences not only offers economic but also ecological advantages [44]. A holistic approach in sheet-metal processing requires to overcome existing data silos and to share data across processes in the sense of an Internet of Production [45].

Another opportunity arises from the combination of the two material monitoring approaches to obtain larger data sets, facilitating the use of data-driven methods to adjust the sheet-metal process to ensure to enable a high-quality process outcome despite fluctuating material properties. Data-driven methods for process optimization and control in sheet metal processing offer the potential to learn complex, unknown interdependencies along process sequences. This leads not only to the optimization of the sheet metal forming process and the quality of the resulting part, but also to the adaptation of upstream processes to specified material requirements based on the previously established dependencies between varying material properties and process parameterization.

In addition, research is mainly limited to sheet metal forming processes, whereas the influence of material variations and a corresponding process optimization has not yet been investigated for sheet metal shearing processes. Hence, there is an opportunity to transfer the solutions presented from sheet metal forming to shearing processes.

Summary

A systematic literature review was conducted showing that there are two different approaches to monitoring fluctuating material properties along coils. It has been shown that non-destructive testing is used successfully inline to measure material properties. Moreover, various methods to monitor material properties in the upstreaming processes hot rolling, cold rolling, roller levelling and stamping were pointed out. The knowledge of material properties along a coil is already used to optimize stamping and deep drawing processes based on different control strategies and research considers fluctuating material properties to optimize different bending processes.

In addition, research gaps were identified: 1) The utilization of knowledge of material properties along coils in relation to the parametrization of sheet-metal forming processes and the outcoming part quality on an industrial scale needs to be investigated in more detail. 2) Further cross-process data exchange is required to research the optimization of downstream processes when fluctuations in material properties occur. 3) The investigation of material variations in sheet-metal shearing processes is still an open topic.

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References

[1] V. Sturm, Einfluss von Chargenschwankungen auf die Verarbeitungsgrenzen von Stahlwerkstoffen, Zugl.: Erlangen-Nürnberg, Univ., Techn. Fak., Meisenbach, Bamberg, 2013.
[2] Y. Xiao, M. Watson, Guidance on Conducting a Systematic Literature Review, J. Plann. Edu. Res. 39 (2019) 93-112. https://doi.org/10.1177/0739456X17723971
[3] D. Harsch, P. Fischer, B. Berisha, J Heingärtner, Y. Renkci, P. Hora, Considering fluctuations of material properties, stainless steel 1.4301, on manufacturability of kitchen sinks, IOP Conf. Ser.: Mater. Sci. Eng. 418 (2018) 12113. https://doi.org/10.1088/1757-899X/418/1/012113

[4] A. Kolhatkar, A. Pandey, Sheet Metal Tooling: Selective Review of Online Monitoring Trends, Int. J. Mech. Prod. Eng. Res. Develop. (IJMPERD) 9 (2019) 183-198.

[5] J. Pennekamp, R. Glebke, M. Henze, T. Meisen, C. Quix, R. Hai, L. Gleim, P. Niemietz, M. Rudack, S. Knape, Towards an Infrastructure Enabling the Internet of Production, 2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS), IEEE. (2019) pp. 31-37. https://doi.org/10.1109/ICPHYS.2019.8780276

[6] U. Engel, M. Schwind, S. Stancu, New Applications of Non-Destructive Testing in Metal Forming Technology, Proceedings of the Institution of Mechanical Engineers, Part B: J. Eng. Manuf. 208 (1994) 259-267. https://doi.org/10.1243/PIME_PROC_1994_208_087_02

[7] J. Heingärtner, M. Born et al., Online Acquisition of Mechanical Material Properties of Sheet Metal for the Reduction of Product Quality by Eddy Current, 10th European Conference on Non-Destructive Testing, Moscow, Russia, 2010.

[8] J. Chen, Z. Fan, An intelligent online detection approach based on big data for mechanical properties of hot-rolled strip, IJMIC 37 (2021) 106. https://doi.org/10.1504/IJMIC.2021.120210

[9] X. Luo, Y. Wang, L. Wang, J. Xie, Y. Zhang, Non-destructive Hardness Measurement of Hot-stamped High Strength Steel Sheets based on Magnetic Barkhausen Noise, Procedia Eng. 81 (2014) 1768-1773. https://doi.org/10.1016/j.proeng.2014.10.229

[10] H. Sheng, P. Wang, C. Tang, Predicting Mechanical Properties of Cold-Rolled Steel Strips Using Micro-Magnetic NDT Technologies, Materials, Basel, Switzerland, 15 (2022). https://doi.org/10.3390/ma15062151

[11] Y. Zhang, W. Liu, K. Li, P. Wang, C. Hang, Y. Chen, X. Han, W. Gao, Application of a back-propagation neural network for mechanical properties prediction of ferromagnetic materials by magnetic Barkhausen noise technique, Insight 61 (2019) 95-99. https://doi.org/10.1784/insi.2019.61.2.95

[12] M. Unterberg, P. Niemietz, D. Trauth, k. Wehrle, T. Bergs, In-situ material classification in sheet-metal blanking using deep convolutional neural networks, Prod. Eng. Res. Devel. 13 (2019) 743-749. https://doi.org/10.1007/s11740-019-00928-w

[13] G. Dobmann, I. Altpeter et al., Industrial applications of 3MA - Micromagnetic Multiparameter Microstructure and Stress Analysis, 5th Int. Conference Structural Integrity of Welded Structures, Timisora, Romani, 2008.

[14] F.J. Alamos, J.C. Gu et al., Evaluating the Reliability of a Nondestructive Evaluation (NDE) Tool to Measure the Incoming Sheet Mechanical Properties, in: G. Daehn, J. Cao, B. Kinsey, E. Tekkaya, A. Vivek, Y. Yoshida (Eds.), Forming the Future, Springer International Publishing, Cham, 2021, pp. 2573-2584.

[15] B. Wolter, Y. Gabi, C. Conrad, Nondestructive Testing with 3MA—An Overview of Principles and Applications, Appl. Sci. 9 (2019) 1068. https://doi.org/10.3390/app9061068

[16] K. Lee, C. Hong, E.H. Lee, W. Yang, Comparison of Artificial Intelligence Methods for Prediction of Mechanical Properties, IOP Conf. Ser.: Mater. Sci. Eng. 967 (2020) 12031. https://doi.org/10.1088/1757-899X/967/1/012031

[17] A. Zoesch, T. Wiener, M. Kuhl, Zero Defect Manufacturing: Detection of Cracks and Thinning of Material during Deep Drawing Processes, Procedia CIRP 33 (2015) 179-184. https://doi.org/10.1016/j.procir.2015.06.033

[18] K. Herrmann, M. Irle, IMPOC: an online material properties measurement system, in: Flat-Rolled Steel Processes: Advanced Technologies, 2009.

[19] G. Nastasi, C. Mocci et al., SOM-Based Analysis to Relate Non-uniformities in Magnetic Measurements to Hot Strip Mill Process Conditions, in: A. Esposito, M. Faudez-Zanuy, F.C. Morabito, E. Pasero (Eds.), Multidisciplinary Approaches to Neural Computing, Springer International Publishing, Cham, 2018, pp. 223-231.

[20] J.M. Allwood, S.R. Duncan, J. Cao, P. Groche, G. Hirt, B. Kinsey, T. Kuboki, M. Liewald, A. Sterzing, A.E. Tekkaya, Closed-loop control of product properties in metal forming, CIRP Annals 65 (2016) 573-596. https://doi.org/10.1016/j.cirp.2016.06.002
[21] X. He, X. Zhou, T. Tian, W. Li, Prediction of Mechanical Properties of Hot Rolled Strips With Generalized RBFNN and Composite Expectile Regression, IEEE Access 10 (2022) 106534-106542. https://doi.org/10.1109/ACCESS.2022.3212053
[22] A. Marmulev, L.M. Kaputkina, G. Herman, E.I. Poliak, Effects of Thermomechanical Processing on Uniformity of Microstructure and Properties of AHSS, MSF 783-786 (2014) 967-972. https://doi.org/10.4028/www.scientific.net/MSF.783-786.967
[23] A. Mukhopadhyay, A. Iqbal, Prediction of Mechanical Properties of Hot Rolled, Low-Carbon Steel Strips Using Artificial Neural Network, Mater. Manuf. Process. 20 (2005) 793-812. https://doi.org/10.1081/AMP-200055140
[24] K. Cuznar, M. Glavan, Optimization of cold rolling process recipes based on historical data, 2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON), IEEE (2022) 1-6.
[25] M. Grüber, G. Hirt, A semi-analytical model for inverse identification of cyclic material data from measured forces during roller levelling, Procedia Manuf. 29 (2019) 420-427. https://doi.org/10.1016/j.promfg.2019.02.157
[26] T. Magro, A. Ghiotti, S. Bruschi, A. Ferraiuolo, An artificial intelligence approach for the in-line evaluation of steels mechanical properties in rolling, Procedia CIRP 100 (2021) 193-198. https://doi.org/10.1016/j.procir.2021.05.054
[27] R.-P. Nikula, K. Leiviskä, Roller Leveler Monitoring Using Acceleration Measurements and Models for Steel Strip Properties, Machines 8 (2020) 43. https://doi.org/10.3390/machines8030043
[28] A. Schenek, M. Görz, M. Liewald, K. Riedmüller, Data-Driven Derivation of Sheet Metal Properties Gained from Punching Forces Using an Artificial Neural Network, Key Eng. Mater. 926 (2022) 2174-2182. https://doi.org/10.4028/p-41602a
[29] H. Kim, J.C. Gu, L. Zoller, Control of the servo-press in stamping considering the variation of the incoming material properties, IOP Conf. Ser.: Mater. Sci. Eng. 651 (2019) 12062. https://doi.org/10.1088/1757-899X/651/1/012062
[30] L. Marretta, R. Di Lorenzo, Influence of material properties variability on springback and thinning in sheet stamping processes: a stochastic analysis, Int. J. Adv. Manuf. Technol. 51 (2010) 117-134. https://doi.org/10.1007/s00170-010-2624-4
[31] N. Okuda, L. Mohr, H. Kim, A. Kitt, Profit-Driven Methodology for Servo Press Motion Selection under Material Variability, Appl. Sci. 11 (2021) 9530. https://doi.org/10.3390/app11209530
[32] D. Briesenick, M. Liewald, P. Cyron, Potentials of an adaptive blank positioning to control material and process fluctuations in deep drawing, IOP Conf. Ser.: Mater. Sci. Eng. 967 (2020) 12068. https://doi.org/10.1088/1757-899X/967/1/012068
[33] B. Endelt, Design strategy for optimal iterative learning control applied on a deep drawing process, Int. J. Adv. Manuf. Technol. 88 (2017). https://doi.org/10.1007/s00170-016-8501-z
[34] B. Endelt, Proposing a new iterative learning control algorithm based on a non-linear least square formulation - Minimising draw-in errors, J. Phys.: Conf. Ser. 896 (2017) 12036. https://doi.org/10.1088/1742-6596/896/1/012036
[35] B. Endelt, J. Danckert, Iterative Learning and Feedback Control Applied on a Deep Drawing Process, Int. J. Mater. Form. 3 (2010) 25-28. https://doi.org/10.1007/s12289-010-0698-z
[36] P. Fischer, D. Harsch, J. Heingärtner, Y. Renkci, P. Hora, A knowledge-based control system for the robust manufacturing of deep drawn parts, Procedia Eng. 207 (2017) 42-47. https://doi.org/10.1016/j.proeng.2017.10.735

[37] P. Fischer, J. Heingärtner, W. Aichholzer, D. Hortig, P. Hora, Feedback control in deep drawing based on experimental datasets, J. Phys.: Conf. Ser. 896 (2017) 12035. https://doi.org/10.1088/1742-6596%2F896%2F1%2F012035

[38] J. Heingärtner, P. Fischer, D. Harsch, Y. Renkci, P. Hora, Q-Guard - an intelligent process control system, J. Phys.: Conf. Ser. 896 (2017) 12032. https://doi.org/10.1088/1742-6596/896/1/012032

[39] B. van Stein, M. van Leeuwen et al., Towards Data Driven Process Control in Manufacturing Car Body Parts, 2016 International Conference on Computational Science and Computational Intelligence (CSCI), 2016.

[40] S. Purr, Datenerfassung für die Anwendung lernender Algorithmen bei der Herstellung von Blechformteilen, FAU Studien aus dem Maschinenbau 338, 2020.

[41] B. Engel, S. Kersten, P. Kopfer, Process-Controlled Forming Using an Intelligent Tool on a Servo Press, Key Eng. Mater. 622-623 (2014) 780-787. https://doi.org/10.4028/www.scientific.net/KEM.622-623.780

[42] P. Lafon, P.A. Adragna, V.D. Nguyen, Multi-objective optimization under uncertainty for sheet metal forming, MATEC Web Conf. 80 (2016) 10004. https://doi.org/10.1051/matecconf/20168010004

[43] R. Waheed, H.A. Saeed et al., Process Optimization of Bending SS 304L Sheets using Multi-Objective Genetic Algorithm and FEA, 2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST), IEEE, 2021, pp. 6-9.

[44] A. Beckers, T. Hommen, M.J.K. Kornely, E. Reuter, G. Grünert, L. Ortjohann, J. Jacob, P. Niemietz, S. Barth, T. Bergs, Digitalized manufacturing process sequences - foundations and analysis of the economic and ecological potential, CIRP J. Manuf. Sci. Technol. 39 (2022) 387-400. https://doi.org/10.1016/j.cirpj.2022.09.001

[45] P. Niemietz, J. Pennekamp, I. Kunze, D. Trauth, K. Wehrle, T. Bergs, Stamping Process Modelling in an Internet of Production, Procedia Manufacturing 49 (2020) 61-68. https://doi.org/10.1016/j.promfg.2020.06.012