INTEGRATING NEURAL NETWORKS INTO SHEET METAL FORMING: A REVIEW OF RECENT ADVANCES AND APPLICATIONS

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Abstract: In order to predict defects, improve performance, and streamline operations, machine learning techniques are becoming ever more indispensable in manufacturing processes, mainly in sheet metal forming. Incorporating neural networks into the process of sheet metal forming is the subject of this article's exhaustive examination of recent developments and applications. Exploring datasets from a variety of sheet metal forming processes, numerous machine learning models, including ensemble and single learning techniques are investigated. The functionality of this method extends to various tasks, including the prediction of springback in cold-rolled anisotropic steel sheets. The review provides a conclusion section that presents the main implementation methodologies and how they address to some manufacturing issues.

Keywords: neural network, sheet metal forming, springback compensation

1. INTRODUCTION

In recent years, the integration of machine learning (ML) techniques, particularly neural networks (NN), into manufacturing processes has gained significant attention, revolutionizing various industries including sheet metal forming [1, 2]. This paper provides a comprehensive review of the latest advancements and applications in leveraging neural networks to enhance sheet metal forming processes. By exploiting the power of artificial intelligence, researchers and engineers aim to predict defects, optimize performance, and streamline manufacturing processes, ultimately leading to improved product quality and efficiency. The utilization of machine learning in manufacturing processes specifically in sheet metal forming is motivated by the need to address complex challenges such as predicting springback, evaluating friction effects, and optimizing cutting processes. Traditional approaches often struggle to cope with the intricacies and variability inherent in these processes. However, with the advent of neural networks, there is newfound potential to tackle these challenges more effectively. One notable aspect of machine learning in sheet metal forming is the adoption of both single-learning and ensemble models. These models are trained using datasets derived from real-world sheet metal forming processes, enabling them to capture the inherent complexities and nuances present in such systems. Ensemble predictive models, in particular, have emerged as a promising approach, offering an efficient means to reconcile model bias and variance, thereby enhancing predictive accuracy.

Various applications demonstrate the versatility and effectiveness of neural networks in sheet metal forming. For instance, predictions of springback in cold-rolled anisotropic steel sheets are made using multilayer perceptron-

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based artificial neural networks coupled with genetic algorithms (GA) [3]. Additionally, neural networks are employed to evaluate temperature-induced friction effects and predict cutting forces in helical end milling processes, showcasing their utility in addressing diverse aspects of sheet metal forming. Innovative manufacturing processes such as single-point incremental forming (SPIF) [4] have also embraced neural networks due to their ability to handle output variability effectively. Furthermore, advancements in laser-engineered net shaping (LENS) [5] have enabled the creation of advanced metal materials, although subsequent grinding processes remain necessary. Machine learning techniques, including artificial neural networks (ANN), play a vital role in optimizing these processes and improving overall efficiency.

Moreover, the integration of machine learning in sheet metal forming extends to areas such as friction modelling, failure prediction, and formability optimization. Neural networks are leveraged to model friction phenomena, predict process parameters, and develop efficient force prediction models. Additionally, they enable the optimization of surface roughness and formability parameters, contributing to enhanced product quality and performance.

The potential of machine learning in sheet metal forming is further underscored by its application in diverse domains such as crystal plasticity simulations, ultrashort laser pulse generation, and welding. These applications highlight the breadth of opportunities presented by neural networks in addressing multifaceted challenges in manufacturing. Overall, the integration of neural networks into stretch-forming represents a significant advancement with far-reaching implications for the industry [4, 6-9]. By harnessing the capabilities of artificial intelligence, researchers and practitioners can overcome longstanding challenges, unlock new opportunities, and pave the way for a more efficient and innovative manufacturing landscape. This review aims to cover chronologically the past 5 years advances and applications in this field, offering insights into the transformative potential of integrating neural networks into sheet metal forming processes.

2. THE NEED FOR PREDICTION

The review consists of various scientific articles related to stretch forming and manufacturing processes [4, 6, 7,10, 11]. The common nominator throughout the research presented is the use of artificial neural networks (ANNs) to improve the prediction and optimization of various aspects of these processes. Neural networks have been used for predicting defects, springback, forces, and friction effects. These applications demonstrate the potential of neural networks to improve the accuracy and efficiency of sheet metal forming processes. Neural networks in stretch forming help in predicting and optimizing various parameters, such as material properties [12], process parameters [13-15], and surface roughness [16, 17].

2.1. Process parameters

Process parameters play crucial roles in the sheet metal forming process [13, 18, 19], including predicting springback [20, 21], evaluating friction effects [14], optimizing forces [4, 22], and enhancing surface roughness and formability [10, 23]. They serve as inputs to machine learning models and simulations, enabling the optimization and improvement of the manufacturing processes.

Recent research in this field offers a high variety of issues that have been addressed, such as predictions of springback of cold-rolled anisotropic steel sheets [24], evaluating temperature-induced friction effects in sheet metal forming [25, 26], incremental deformation in manufacturing processes [4, 8], superplastic forming in aluminium forming [27], flow stress of TI-6AL-4V during hot deformation [26, 28], research on friction coefficient with artificial neural networks [14], machine learning in manufacturing and sheet metal forming, uniaxial tension tests on aluminium alloy 6016-T6 [29], drawbead simulator for determining their shape and coefficient of friction [30-32], failure prediction in sheet metal forming design [32], the influence of sheet forming process parameters on surface roughness [16, 17], a machine learning method for hardening law of aluminium alloy sheets in manufacturing processes [33], data-driven methodology for high-velocity forming (HVF) [34], use of data science methods in manufacturing processes, deformation behaviour of metal materials in plastic forming [35], AI for springback compensation in hairpin forming [20], adopting adaptive neural network fuzzy inference system (ANFIS) [23], proposing a machine learning-based constitutive model for anisotropic plasticity in sheet metals, optimizing the formability of sheet metals, evaluating formability of AISI 316 steels [9], scalar-based surrogate models for sheet metal forming [36], crystal plasticity theory in sheet metal forming [37], grain size in sheet metals and formability [23], or machine learning material models (MLMM) [12, 38].

2.1. Generated data and prediction complexity

The training of an NN starts with the generated or recorded data [38]. To generate data prediction for stretch forming, there has to be identified all of the relevant process parameters. The NN outcome is correct only if relevant data is fed into the training process. For this to happen complex and reliable measurement systems are used. Such measurements can include an inline-measurement system integrated into a production tool [24], numerical simulation using finite element methodology (FEM) [8, 38-40], data acquirable in real physical experiments (uniaxial tensile test, sheet processing data) [41].

A regression model and an artificial neural network model were built to determine the complex interactions between the process parameters and the friction coefficient [31], a genetic-algorithm-based multi-objective method to maximize forming height, minimize thinning rate, and obtain the optimum process parameters [3], optimization algorithms in neural networks to maximize the formability of sheet metals based on a tensile curve and texture of aluminium sheet metals [11, 23], the coefficient of friction (COF) value was determined using the Random Forest machine learning algorithm and artificial neural networks (ANNs) [30, 42], image-based optimization architecture [43], along with a differential evolution algorithm with self-adaptive factors [23, 41], Levenberg-Marquardt training algorithm performed the most effectively in predicting wall diameter and pillow effect [44], multiplayer perceptron's trained by backpropagation [3], Levenberg-Marquardt algorithms favour punch bend depth under load as the most important variables affecting the springback coefficient [19, 45], and the flow stress of Ti-6Al-4V during hot deformation was modelled using a decision tree algorithm [28].

3. INTEGRATION OF NN'S

In 2020 M. Dib el. al, proposes a machine learning approaches for predicting defects in sheet metal forming processes, including ensemble predictive models and single classifiers [1]. In the same year, T. Trzepiecinski and G. Lemu Hirpa make prediction of springback of cold-rolled anisotropic steel sheets using a multilayer perceptron-based artificial neural network (ANN) and genetic algorithm (GA). The study finds that specimens cut along the rolling direction show higher springback coefficient values, while Young's modulus and ultimate tensile stress have no significant effect on the springback coefficient [3]. K. Matthous et. al, research is on observability and controllability of temperature-induced friction effects in sheet metal forming processes, focusing on the integration of an inline measurement system into a production tool to gather data for a tribology-based control system. Multilayer artificial neural networks are trained to evaluate the measurement system and identify potential further measurements within the process [25]. The development of a new high-strength Al-Zn-Mg-based alloy for superplastic forming is presented by O. Yakovtseva et. al. in "High Strain Rate Superplasticity in Al-Zn-Mg-Based Alloy: Microstructural Design, Deformation Behaviour, and Modelling"; the alloy which provides superplasticity with an elongation of 600-800% in a strain rate range of 0.01 to 0.6/s and less than 2% residual cavitation. The superplastic flow behaviour of the alloy is modelled via a mathematical Arrhenius-type constitutive model and an artificial neural network model [27].

The study "Assessment of the effectiveness of lubrication of TI-6AL-4V titanium alloy sheets using radial basis function neural networks", by T. Trzepiecinski and M. Szpunar, published in 2021, investigates friction coefficient value and empirical model building using radial basis function artificial neural networks. Tests were conducted on a friction simulator with sheets of Ti-6Al-4V titanium alloy, including variable contact forces, rounded surfaces, and various lubrication conditions. The coefficient of friction (COF) value was highest for average values of nominal pressure and kinematic viscosity. SAE10W-40 engine oil ensured the most effective reduction of COF [46]. Research work also explore the capability of shallow artificial neural networks (ANN) for identifying material constitutive model parameters and predicting punch displacement in sheet metal press-brake air bending [12, 45]. In another paper by T. Trzepiecinski and M. Szpunar friction phenomena is researched by using artificial neural networks models, with the Levenberg-Marquardt algorithm being the best fit for regression [47]. Two latest constitutive models: modified Arrhenius (m-A) and combined Johnson-Cook and Zerilli-Armstrong (JC-ZA) ware used for predicting flow stress, while the Marciniak-Kuczynski model was used for predicting forming limits; this model proposed by A. Morchhale et. al in 2021 and it was concluded that artificial neural networks (ANN) are more accurate and versatile than dimensional analysis models in predicting forming limits [26]. Machine learning was used by S. Athreya et. al. for design optimization in progressive die stamping, with a surrogate model based on an artificial neural network, achieving an accuracy of 5%. These studies provide important insights into the use of AI and machine learning in various industries [36].

Drawbeads are used to adjust flow resistance or stress in complex shapes. In 2022, T. Trzepiecinski and S. Najm propose in their paper “Application of artificial neural networks to the analysis of friction behaviour in a drawbead profile in sheet metal forming” a methodology, using artificial neural networks (ANNs), to understand the impact of friction process parameters on friction coefficient. The friction coefficient was determined for low-carbon steel sheets with various drawability indices. Tests were conducted under dry friction conditions and lubricated with machine oil LAN46 and hydraulic oil LHL32. Various specimen orientations and surface roughness values were considered. The coefficient of friction increased with increasing surface roughness of counter-samples. The study used backpropagation in an MLP structure and Garson partitioning weight to calculate the relative importance effect on coefficient of friction. The Bayesian regularization backpropagation (BRB)-Trainbr training algorithm and the radial basis normalized-Radbasn transfer function were the best predictor [31].

In 2022, sheet metal forming design failure prediction is researched by I. El Mrabti el. al. [32].The research paper “A comparative study of surrogate models for predicting process failures during the sheet metal forming process of advanced high-strength steel” conducts and investigation of four common surrogate techniques: Response Surface Methodology (RSM), Radial Basis Function (RBF), Kriging, and Artificial Neural Network (ANN). The training data was obtained by developing of a finite element model (FEM) to predict thinning and fracture [32]. The deformation behaviour of metal materials in plastic forming is influenced by deformation rate, forming temperature, and plastic variables. Three models were analysed: the phenomenological constitutive model, the microscopic constitutive model, and the artificial neural network constitutive model. This work, presented in a review paper “Plastic deformation behaviour of metal materials: A review of constitutive models” by J. Xiangdon el. al. indicate that macroscopic mechanical properties research is crucial for analysing process parameters and deformation process of metal plastic forming, and understanding the influence mechanism of macroscopic mechanical properties is crucial to establish material constitutive models under different deformation conditions [35]. Z. Yumeng et. al. proposes an industrial production monitoring with artificial intelligence was proposed using a transfer learning-based Stacked Auto-encoder (SAE) with Convolutional Neural Network (CNN), which improved performance and suggested the potential for pattern recognition in sheet metal forming processes [48].

In 2023, the friction coefficient is studied from other perspectives. One of them is the CatBoost machine learning algorithm used for modelling and parameter identification of friction coefficients for three grades of deep-drawing quality steel sheets. Input parameters included lubrication conditions, normal force, and surface roughness of counter sample surfaces. Different transfer functions and training algorithms were tested to build the optimal structure of artificial neural networks. An analytical equation was created to calculate the coefficient of friction of each material. The Levenberg-Marquardt training algorithm performed the best in predicting the coefficient of friction [14]. Another approach is proposed by T. Trzepiecinski et. al. in their paper “Analysis of the Frictional Performance of AW-5251 Aluminium Alloy Sheets Using the Random Forest Machine Learning Algorithm and Multilayer Perceptron” on the determination of the coefficient of friction (COF) in the drawbead region in metal-forming processes. Experimental tests were carried out under conditions of dry friction and lubrication of sheet metal surfaces with three lubricants: machine oil, hydraulic oil, and engine oil. The Random Forest (RF) machine learning algorithm and artificial neural networks were used to identify the parameters affecting the COF [42].

The research conducted by M. Zhang et. al. examines the formability of AISI 316 steels, focusing on the microstructure that affects their formability. Austenitic steels with strain-induced martensite (a-martensite) cause hardening and formability reduction. Relative area of strain-induced martensite measured using metallography tests, while forming limit diagrams (FLDs) were obtained using hemisphere punch test. The data was then used to train and validate an artificial neural fuzzy interfere system (ANFIS), that shows satisfactory results compared to experimental measurements [9].

The study investigates the impact of anisotropy on sheet metal forming, focusing on its influence on the metal's crystallographic structure and rolling process. Crystal plasticity theory accounts for anisotropic elastic tensor and crystallographic deformation mechanisms. High computational costs hinder integration of crystal plasticity theory in macro simulations. Machine learning approach aims to rectify this issue with the use of the DAMASK simulation package. The study also explores springback compensation in sheet metal components using the finite element method and artificial neural network, with nine experiments designed considering three process parameters. A phenomenological material model for an AA5083 aluminium alloy provided training data for neural network study [37]. Another approach is the study of the grain size's impact on formability in sheet metals, as grain size is considered key factor in determining formability in sheet metals [23]. The study conducted by N. Yang et. al. in 2023 uses design of experiment (DoE) and artificial intelligence (AI) methods to find optimal grain size conditions and predict forming limits. Experiments provide initial data for training and testing DoE and AI. The response surface method (RSM) is used to calculate the optimum grain size, and the trained neural network predicts formability under the calculated optimum condition. The results indicates that DoE and AI can aid in designing, determining, and predicting optimum grain size for sheet formability [23].

4. CONCLUSIONS

This article explores the use of neural networks in different aspects of sheet metal forming processes. It focuses on their ability to predict defects, springback, friction effects, and deformation behaviour. Moreover, advanced algorithms were implemented and proven to be effective in solving problems such as: defects identification parameters (parameters related to defects in sheet metal forming processes, such as surface irregularities, cracks, wrinkles, and deformations), material properties (characteristics of the sheet metal material, including its composition, thickness, mechanical properties, and anisotropy), process conditions (parameters related to the forming process, such as temperature, pressure, strain rate, tooling design, and lubrication), quality metrics (used to evaluate the performance of the NN models in defect prediction, such as accuracy, precision, recall). These process parameters are essential for developing accurate and reliable machine-learning models for defect prediction in sheet metal forming processes.

The review has emphasized the use of artificial neural networks (ANNs) in predicting the springback of cold-rolled anisotropic steel sheets. The research has identified the punch bend depth under load as a crucial variable that affects the springback coefficient. In addition, artificial neural networks (ANNs) are used to analyse friction tests, build empirical models, and predict surface roughness. These applications showcase the high accuracy and strong correlation with measured data. In addition, the review explores the advantages of using ANNs instead of dimensional analysis models to forecast forming limits and deformation force in sheet forming techniques. The application of machine learning technologies in design optimization highlights the adaptability and efficiency of neural networks in enhancing manufacturing processes. In addition, the combination of neural networks with other modelling techniques like finite element analysis and symbolic regression to improve the discovery of process knowledge and enhance prediction accuracy. Neural networks have become essential tools in advancing sheet metal forming engineering, helping to optimize sheet metal formability and address challenges such as springback compensation and formability reduction in specific materials. Thus, this paper highlights the significant contribution of neural networks in enhancing the comprehension, forecasting, and enhancement of different aspects of sheet metal forming processes. This progress opens up opportunities for more streamlined and productive manufacturing methods.

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