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Artificial intelligence in metal forming

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ABSTRACT

Forming processes are known for their intricacies in prediction and control due to the complex loading conditions and material flow. This paper will first introduce the AI algorithms used or having potential to be used in forming, and then investigate the state-of-the-art advances of AI-based technologies in forming processes with four main pillars of process simulation, process design and optimization, in-situ process control, and qualification and certification of forming processes and formed products. Future directions of AI in forming for both academic research and industrial applications will be proposed to leverage digitalization and data science to explore new solutions in forming processes.

1. Introduction

The goal of metal forming is to create a metallic part with the desired shape, dimensions, and properties to meet with multi-mode functional requirements, such as lightweighting and structure stiffness in automotive and aerospace applications, fitness in patient-specific biomedical devices, flexibility in electronics switches, toughness in swords, etc. Meanwhile, the production volume of a metal formed product can vary from one single piece to millions. Correspondingly, metal forming has enormous degrees of freedom in process design (temporal and spatial design of strain path, stress state and temperature history, to name a few), which makes metal forming an attractive and promising unit manufacturing process for many applications. On the other hand, the difficulty in physically measuring local material states, the existences of high tooling cost in mass production applications or the combination of long forming time and localized deformation zone in incremental metal forming for low production volume applications, pose significant challenges for process engineers and practitioners.

Analytical models involving first-order [253] and second-order yield criteria [109,261], slab method [221], upper bound method [15] up to late 1960s have been widely used to estimate forming forces to assist process design. Finite element methods (FEM) have evolved rapidly over half a century since then and nowadays enable the simulation of almost all kinds of forming operations before tools are built in mass production [9,172,260,271]. However, their applications in process design and in predicting the resulting material behavior and part performance in increment forming (IF) have been limited due to the orders of long forming time in IF compared to that for mass production. To some degree, the simulation challenges of IF processes are similar to that for additive manufacturing (AM), in which deformation or process physics mainly occurs in the scale of micrometer to millimeter while the entire part can be in the meter scale, i.e., posing general challenges to full-scale high-fidelity simulations. Due to the large number of layers and scan vectors per layer, full-scale pure physics-based simulation of processes such as laser powder bed fusion is far beyond reach [205]. However, since AM does not involve any tooling and the full explosion of active working surface to cameras (optical for imaging or photodiode for heat intensity) due to its layer-by-layer operation nature that can easily generate 10x GB to 1 TB data for one production run, and since actual process executes orders of magnitude faster than a high-fidelity simulation, a rich variety of data-driven machine learning methods have been developed for AM [94,184].

In metal forming, in contrast, the majority of material states are invisible from external sensors due to the employment of tool. Research efforts have been made for developing sensors to measure force and relevant material flow to support efforts of process monitoring and quality control [8]. Nevertheless, large data sets (particularly local information) are difficult to generate in-situ. Unlike a mathematical model is created first by a user and then examined in the statistics approach, a model is created by the algorithm in artificial intelligence (AI) based on the data. This essential difference makes AI both attractive and doubtful. Similar to the historical moment in 1960s where FEM started to emerge and benefit the forming community tremendously due to the increasing computational power offered by the semiconductor industry, today, the questions are what AI can do for the metal forming community and what research and development that the metal forming community should work on to leach the potential benefits and to avoid the unphysical results of AI to improve efficiency, reduce costs, and ensure product quality. These two critical questions will be addressed from the perspectives in the sections as illustrated in Fig. 1.

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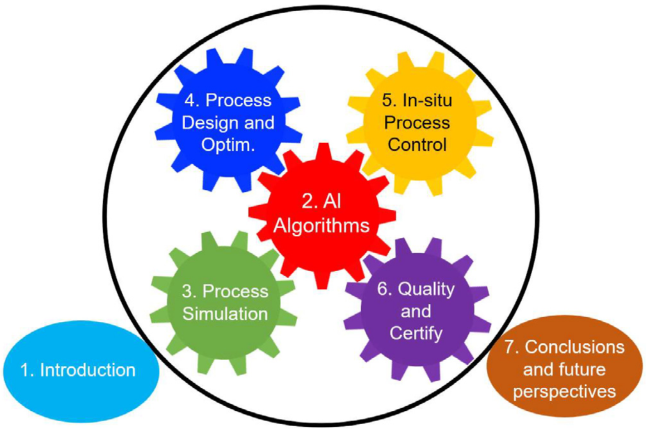

Fig. 1. Schematic of key discussion topics in this paper.

1.1. AI algorithms (Section 2)

Since this paper is the first review article on AI in forming, various AI algorithms that have been applied to (such as various neural networks structures) or have the great potential to be applied (such as natural language processing (NLP)) to metal forming problems are summarized. Key features and differentiations will be discussed to provide readers with fundamental knowledge to participate in the following discussions.

1.2. Process simulation (Section 3)

Process simulation is an essential tool in process design and optimization and in understanding and the interpretation of measured data. The effectiveness and usefulness of a process simulation depends on its accuracy and speed. The state of the art in using AI in process simulations, including models of plastic deformation, damage, and forming limits will be surveyed and compared to 'conventional' finite element simulation methods in terms of speed and general applicability.

1.3. Process design (Section 4)

The essence of process design is an optimization problem, which involves the design of forming tool, the design of blank geometry, and the design of process parameters (deformation path, temperature profile, forming rate, etc.). Traditionally the design process heavily depends on the experience of a designer or handbook. Process simulations have been used in the forward analysis mode to provide information needed for the designer to make decisions. AI algorithms used to analyze data from metal forming processes and identify opportunities for improvement will be reviewed. It is also possible to 'invert' process models by training algorithms that map from output to input, which allows for fast process optimization.

1.4. Process control (Section 5)

One most widely, and probably the earliest, application of AI algorithms in metal forming is for process control. The controllers built on models established by neural networks will be reviewed. Furthermore, a fundamental distinction existed between approaches in sheet metal forming, bulk metal forming and joining technology, which will be elaborated in detail in this section.

1.5. Qualification and certification (Section 6)

The current practice and standard of qualification and certification can significantly add to the manufacturing cost and prolong the development of new products, particularly with new materials. For AM, this is a major hurdle. For flexible incremental processes (e.g., open die forging), the similar challenge exists, such as how to accurately know the local material properties and then effects to the overall part quality. For mass production processes, as tool wears the resulting part quality will be different. AI algorithms can be used for quality control inspections and identify patterns that may indicate problems with the mass production process so that predictive maintenance can be performed.

1.6. Future research and development (Section 7)

A hybrid physics-based and data-driven approach that links material's microstructure to processing condition and part performance can be promising for many aspects discussed above. Additionally, there have been tremendous tacit knowledge accumulated in our metal forming community. Exploring NLP for metal forming will be an interesting research direction. A total of ten (10) represented directions are listed to encourage our metal forming community to explore.

The goal of any manufacturing action is to increase its market competitiveness, which can be measured by a number of metrices, including quality (ultimately zero defects or first-time right), time-to-delivery, minimum adverse environmental impact, cost, and social impacts. These metrices are not the result of a single technical area, but of multiple perspectives. Discussions will be woven into the following sections with the aim of providing systematic assessments on the demonstrated advantages and challenges of using AI in metal forming. Finally, to facilitate cross-referencing and to bring readers, regardless of their familiarities with AI methods or forming processes, to a common base, Table 4 summarizes the abbreviations used in this paper.

2. Overview of AI algorithms used in metal forming

Artificial intelligence (AI) broadly refers to computer programs that automate tasks associated with human thinking, such as perception, problem-solving, and planning [22]. Since the first application of artificial intelligence in 1952, a checker program, AI (see [218,227] for taxonomy) has transformed several industries, especially in the fields of natural language processing, computer vision, and recommendation systems. Much of these advances are owed to the drastic progress in Machine Learning (ML), a subfield of AI, where computer programs can learn directly from data. This paradigm is in contrast to programs with explicitly coded rules and instructions [228]. ML methods are commonly categorized into three classes based on the type of data they work with: supervised, unsupervised, and reinforcement learning, working with labelled, unlabelled, and interactive data, respectively. However, techniques such as semi-supervised, self-supervised [86], and contrastive learning [197,280], as well as the widespread adoption of supervised methods for reinforcement learning problems, have blurred the distinction between the mentioned three classes. Three typical supervised ML algorithms are summarized in Table 1 with their characteristics for comparison. Note

Table 1
Summary of typical supervised ML algorithms.

	Linear models	Tree-based methods	Artificial neural networks (ANN)
Algorithms	Linear Regression, Logistic Regression, SVM	Decision Tree, Random Forest, CART	FCNN, CNN, RNN, GNN
Input Data Types	Numeric, Categorical	Numeric, Categorical	Numeric, Image, Text, Audio, Video
Data Amount Needed	Medium	Medium	Large
Training Speed	Moderate	Moderate	Slow
Explainability	Interpretable w/ Linear Kernel	Low to Moderate	Complex
Typical Applications	Classification, Regression	Classification, Regression	Image Recognition, NLP, Time Series Prediction, Sentiment Analysis, Speech Recognition, etc.

that one metal forming process typically features multiple perspectives that can benefit from ML, for example, classification for tool design, regression for force prediction, image recognition for wear detection, etc.

The workhorse behind ML is a set of statistical tools that allow parametrized function approximation given observed data. **Linear models,** such as **Linear regression, logistic regression**, and **support vector machines** (**SVMs**) provide efficient solutions when dealing with linear relationships. SVM can be also used to classify data into different categories. However, their linear bias makes these methods highly reliant on hand-crafted feature engineering and limits their capability to capture unintuitive interactions in the data. Still, linear models are good options when high-quality features are available, data is limited, or when fast re-training time, inference time, and high explainability are desired. **Tree-based methods**, such as **Decision trees, Random Forest**, and **Classification and Regression Trees (CART)**, provide prediction models based on explainable decision trees. Decision trees allow to make predictions based on a series of rules or conditions. Random forests or CART combine multiple decision trees to make more accurate predictions. They are particularly powerful in applications with tabular databases with moderate complexity. However, when dealing with large databases, non-tabular information, and complex problems, **artificial neural networks (ANN)** often outshine other ML methods. This is due to their computational scalability allowing the training of enormous networks (with some recent models having hundreds of billions of trainable parameters [34,241]) and configuration flexibility to work with all data types (e.g., tabular, time-series, image, audio, video, graphs). Artificial neural networks are a type of machine learning algorithm that are inspired by the structure and function of the human brain. Due to the popularity of NNs, below details of NNs will be introduced.

Some of the most commonly used neural network types are shown in Fig. 2. A fully connected neural network (**FCNN**) performs a matrix multiplication of input data with trainable hidden state parameters, followed by a nonlinear activation function. In theory, even one layer of FCNN can approximate any function [111]; however, in practice several of such layers are stacked on top of each other (i.e., the output of the one FCNN layer is fed as the input into another layer) to capture nonlinearity in the data. FCNNs work with fixed-size tabular data and are common building blocks of many neural network architectures.

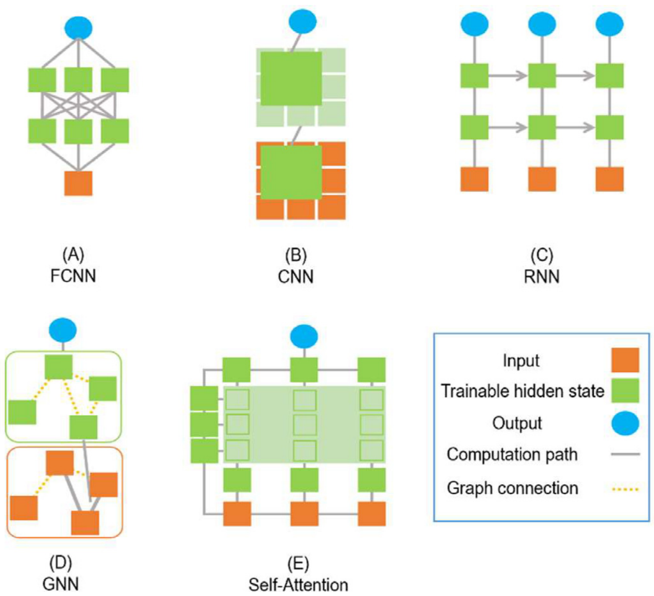

Fig. 2. Schematics of popular neural networks including (A) fully connected neural network, (B) convolution neural network, (C) recurrent neural network, (D) graph neural network, and (E) self-attention network.

A convolutional neural network (**CNN**) computes the dot product of a kernel, e.g., a 3×3 grid of trainable parameters, with different patches of the input data (often images) to create output patches. As the result of this design, CNNs are translation-invariant—meaning one kernel can detect a feature regardless of its position in the image. Nonlinear activation function, pooling (i.e., combines values of neighboring pixels), and stride (i.e., controls the sliding distance of kernels) are other standard CNN components. CNNs have been the dominant method in image, video, and sound processing due to their inductive bias toward extracting local information at multiple scales. They can potentially identify patterns and trends that may not be apparent to humans.

Recurrent neural networks (**RNN**) are designed to process time-series and sequential data. A RNN cell at a given time step receives the input for that time step along with its own output (or history state) from the previous time step and produces a new output. While a naïve implementation of this idea leads to poor gradient propagation, several successful formulations are proposed to largely mitigate this problem. For instance, Long-Short Term Memory (LSTM) [110] replaces matrix multiplication and nonlinearity along the gradient pass of adjacent RNN cells, with gated mechanisms that instead create element-wise multiplication and addition operations along the gradient pass and, hence, is less prone to vanishing or exploding gradients.

Graph neural network (**GNN**) benefit from a unique capability to process unstructured graph-based data [50,135]. While there are many formulations proposed for GNNs, they often consist of three components: (1) creating messages between adjacent graph nodes, (2) aggregating the incoming messages for each node, and (3) updating the nodal (or elemental values) given the aggregated message, where the computations in steps (1) and (3) are performed using FCNNs or other neural network types. GNNs are particularly well-suited for analyzing social networks, geometries, and chemical elements.

Self-Attention is a type of neural network [258] where an attention score is computed for each input-output pair and is used to determine relevant parts of the input for each output prediction. Self-Attention was originally developed to tackle the language-to-language translation problem but quickly found its way as the state-of-the-art approach in tasks across language modeling [34,52], vision [60,120], and decision-making [40]. This is due to their versatility to work with different types of data (e.g., sets, time-series, tabular), capability to work with long sequences without forgetting inputs far from the output, and massive parallelization capability that fits well with modern deep learning hardware.

2.1. Deep learning

Deep learning is a subset of machine learning that uses neural network exclusively, which became practical due to the birth of the GPU hardware [140]. Using the backpropagation algorithm [217], modern deep learning libraries (e.g., PyTorch [204], TensorFlow [1], JAX [30]) can efficiently compute gradients of a user-defined loss function with respect to trainable parameters of any neural network type and minimize the loss using variations of stochastic gradient descent optimization. Nowadays, several numerical and optimization practices are standard elements of a neural network training process, including regularization techniques to avoid overfitting (e.g., dropout, batch normalization, layer normalization), learning rate scheduling to stabilize the training, initialization methods and residual connections to allow deeper networks, sampling methods to battle unbalanced data, and specialized loss formulations for many downstream tasks. The collection of these practices allows reliable training of enormous neural network systems.

The computational convenience and the merge of powerful modern deep learning libraries have sparked the usage of NNs in more sophisticated ways that goes beyond just "curve fitting to data". Scientists have built higher level methods on top of the neural network building blocks (e.g., Fig. 2) to solve many engineering problems. Physics-informed neural networks (PINNs) are specifically designed to solve problems in which the solution is governed by physical laws or constraints. In a PINN originally proposed in [212], the neural network is trained to approximate the solution to a partial differential equation (PDE) as a surrogate model that describes the physical system of interest. The network is trained to satisfy the PDE constraints at a set of points called the 'collocation points', which are chosen based on the characteristics of the PDE and the desired accuracy of the solution. One advantage of using a PINN to solve a PDE is that it can handle problems with high-dimensional input spaces and complex boundary conditions, which can be difficult to solve using traditional numerical methods. Additionally, PINNs can be trained using data from experiments or simulations, allowing them to incorporate additional information about the physical system into the solution. However, in pure physics-based simulation tasks, PINNs are found to be not as efficient as traditional methods like the finite element method [93]. Solution behaviours such as sharp gradient or discontinuity are hard to approximate with PINNs [63].

Generative adversarial networks (GANs) are deep learning algorithms that can be used to generate new data that is similar to a training dataset. GANs consist of two neural networks, a generator and a discriminator, that are trained together in a competitive process. The generator network tries to generate synthetic data that is similar to the training data, while the discriminator network tries to distinguish between the synthetic data and the real training data. GANs have been applied to problems related to metal forming and plastic deformation. For example, GANs have been used to generate synthetic data that can be used to train other machine learning algorithms for tasks such as predicting the deformation behavior of materials under different loading conditions. However, training GANs is known to be hard due to mode collapse, instability, and sensitivity to hyperparameters [225]. In the past three years, the family of denoising diffusion probabilistic models (DDPMs) [53] have emerged as powerful generative AI methods that are replacing many of previous state-of-the-art models such as GANs.

Finally, expert systems are a type of AI that are designed to mimic the decision-making abilities of human experts in a particular domain. They consist of a knowledge base, which contains information about the domain, and an inference engine, which uses this knowledge to solve problems or make decisions. In metal forming, expert systems have been used to optimize the process parameters of metal forming processes, such as the temperature, strain rate, and tool geometry. By using expert systems, it is possible to make more informed decisions about these parameters, based on the knowledge and experience of human experts in the field. A rising popular program, ChatGPT of OpenAI launched in November of 2022, uses natural language processing and reinforcement learning (RL) from human feedback to train the model through three steps: collect demonstration data and train a supervised policy; collect comparison data and train a reward model; and optimize a policy against the reward model using the reinforcement learning algorithm. Although its applications in metal forming may be seen as far-fetched at this moment, the capabilities of ChatGPT have been demonstrated as a powerful tool for composing articles and software programs.

3. AI for simulating metal forming processes

Numerical simulations of metal forming processes have played an essential role in shortening the development cycle from design to production, i.e., about 48 months in early 1990s to 18–21 months in 2020s. Such simulations aim to predict material behavior and the workpiece-tool interfacial behavior subject to external thermal and mechanical loading histories, which has three essential elements, i.e., material constitutive behavior (stress and strain/strain-rate relationship), failure prediction (e.g., necking and fracture, buckling, and tool wear), and contact and friction modelling. The overall system needs to satisfy the mechanical and thermal governing equations built upon the quasi-static (or dynamic) equilibrium and the heat transfer equations. Below the applications of AI in constitutive modelling (Section 3.1), failure prediction (Section 3.2), and interface and system modelling (Section 3.3) will be reviewed.

3.1. AI for constitutive modeling

Modern materials are integral parts of today's technology and advancing our understanding of them helps to produce better engineering products. However, characterizing material behaviors under complex loading conditions of forming processes has remained an ongoing challenge. Despite decades of significant progress in simulating material models using computational plasticity, crystal plasticity, and integrated computational materials engineering (ICME) approaches, one still cannot accurately simulate or design materials in many realistic large-scale high-volume manufacturing applications. For example, in computational plasticity, three-dimensional inelastic phenomena are commonly reduced to a so-called "effective" representation space, in which the material response is developed using a combination of theoretical and phenomenological laws, such as yield surface evolution [17] and associative or non-associative flow rules [168]. While such formulation can lead to effective ways to characterize material response, these assumptions can be too restrictive for predicting intricate behaviors of today's advanced alloys, such as anisotropy [18,108], ratcheting [36,196], distortional hardening [16,72,78], and permanent softening [85]. Decade-long research efforts have introduced sophisticated responses into material models [149,174]; however, with them, the complexity of computational material modeling grows substantially, leading to prohibitively expensive models that take days or even weeks of computational time.

As manufacturing is moving toward digitalization with large volumes of in-situ and ex-situ sensing methods, new opportunities arise to learn complex material behavior using advanced data-driven techniques. As opposed to conventional physics-based material modeling methods that are heavily based on analytical and phenomenological material laws, data-driven material modeling methods offer a more flexible formulation that can capture nuance behaviors of broader ranges of materials. However, several challenges remained to be addressed before data-driven material modeling can be used as a reliable tool in engineering practices.

- Most studies are solely dependent on computationally generated databases which themselves rely on conventional material modeling and do not offer a solution to resolve the computational artifacts seen in conventional FEM (e.g., the artificial wrinkling in ironing simulations). These factors can lead to substantial *inaccuracies*, especially in forming applications where critical characteristics such as formability and tear-off might occur as the material undergoes large deformations.
- The flexibility of data-driven material modeling methods can come at cost of a lack of *instability* and numerical guarantees when integrated into part-scale analyses. Rigorous investigations into numerical properties of such solutions when integrated into part-scale and multi-scale settings are vital to the progress of this field. Explicit solvers are the standard approach in many engineering applications, especially in sheet metal forming, as they scale well to large problems and can handle challenging contact behaviors. Therefore, the compatibility of data-driven methods with explicit solvers is an important topic.

While the computational efficiency and accuracy of deep learning models have been demonstrated for simplistic "toy examples" in the literature, the capability of these models at the *scale* of practical manufacturing parts is yet to be proven.

Here, a critical review of the current state of data-driven material modeling methods is presented and categorized based on their fundamental properties, and the advantages and shortcomings of each method are discussed. Existing methods in the literature are classified based on two criteria of computational paradigm (i.e., the

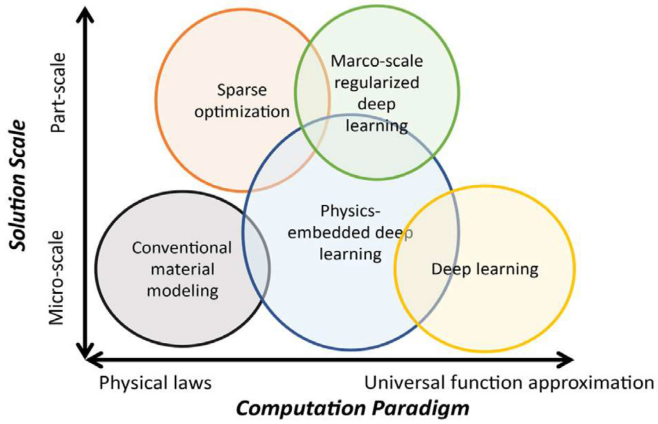

Fig. 3. Landscape of data-driven material modeling methods analysed in two dimensions of computation paradigm (amount of hard-coded physics involved) and their operating scale (micro-scale vs part-scale).

amount of hard-coded insights versus learnable features in the model) and the scale at which they operate (i.e., micro-scale or part-scale). As depicted in Fig. 3, four major classes of data-driven material modeling methods in the literature are observed which include: pure deep learning methods, physics-embedded deep learning, macro-scale regularized deep learning, and sparse optimization methods.

3.1.1. Deep learning

In recent years, pure data-driven material modeling was shown to be a viable alternative to conventional modeling methods. While many machine learning approaches can apply to this problem, deep learning methods have been dominant in pushing the frontiers of material modeling. This is because neural networks offer high expressiveness in capturing non-smooth and sharp transitions, relatively robust ill-distributed data, perform well in high dimensional spaces, and can be flexibly configured (e.g., to capture history-dependency). In this class of methods, constitutive models and dynamic structural equations are decoupled, and micro-scale or representative volume element (RVE) scale constitutive model aims to find a mapping between local deformations as the input and stresses (along with other measures such as energy, damage, and failure) as the output. In [182], Mozaffar et al. developed a deep learning RVE-scale approach based on the recurrent neural network (RNN) to capture elasto-plastic behaviors of materials with particle inclusions under arbitrary loading conditions (see Fig. 4). It was shown that the data-driven model can learn the stress-strain mapping accurately and implicitly learn complex interdependencies between yield surface and hardening, such as highly distortional hardening behavior, within 0.5% error. Gorji et al. [88] expanded on this approach with a focus on the Bauschinger effect and stress overshooting for aluminum and steel alloys.

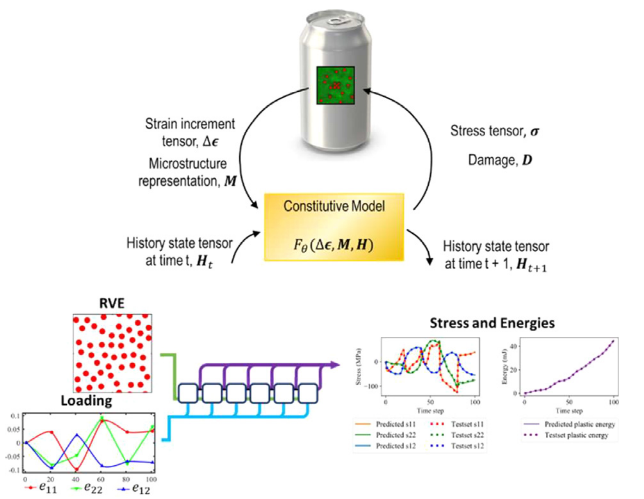

Fig. 4. Pure deep learning approach for RVE-scale material modeling predicts history-dependent material response for materials with particle inclusions. The interaction of macro-scale dynamic structural solver and micro-scale constitutive material model (top), and the inputs and outputs of neural networks-based material model (bottom) are depicted [182].

Wu et al. [267] took a similar approach, i.e., supervised learning using conjugate stress-strain pairs, and presented a successful implementation of a recurrent neural network-based material model within the implicit solver of multiscale finite element simulation, which led to four orders of magnitude speed up in online computational cost. In [272], yield surface evolution is predicted using supervised data-driven modeling, which is later used to solve the boundary value problem in elastoplastic constitutive laws of materials with heterogeneous microstructures. Other researchers have extended the application of the micro-scale data-driven constitutive modeling using conjugate stress-strain pairs to thermo-visco-plastic behavior of steel [4], visco-elastic materials [38], multi-phase solids [87], and homogenization of short fiber reinforced composites [31].

Liu et al. [160] deployed a neural networks-based constitutive material model that was trained on top of micro-scale crystal plasticity simulations into macro-scale models for 3D inelastic impact problems with an explicit user material subroutine (VUMAT) implementation, though without capturing history-dependencies. Ali et al. [7] trained a fully connected neural network (FCNN) model using the data generated from a rate-dependent crystal plasticity finite element simulation to predict the stress-strain and texture evolution of AA6063-T6. The runtime comparison test showed that the developed model saves more than 99.9% of the computational time compared to the conventional crystal plastic model. Ibragimova et al. [117] designed a framework where an ensemble of fully connected neural networks (FCNN) were trained with a dataset of crystal plasticity simulations to model the stress-strain relationship and texture evolution for face-centered cubic (FCC) family crystals under a non-monotonic strain path [98].

Despite the progress made in this newly emerging field, pure deep learning-based material modeling suffers from three main shortcomings. First, the training of neural networks requires stress-strain pairs which are rarely experimentally available. Therefore, this approach is mainly useful in multi-scale settings where a reliable micro-scale simulation is available. Second, as the training is solely dependent on externally provided data, it often requires tens of thousands of data points to be sufficiently trained for most interesting cases. Third, pure data-driven methods offer little guarantee on the behaviors of materials. While pure data-driven material modeling is shown to be applicable for part-scale implicit solutions, as implicit time integration is inherently stable, it can easily lead to instability in explicit solutions. Bonatti et al. [27] propose a RNN architecture that integrates self-consistency in its definition based on solid understanding of the physics between strain increment and stress increment. They successfully demonstrated explicit FEM executions using this model.

3.1.2. Physics-embedded deep learning

To overcome the challenges of purely data-driven methods, recent research efforts have attempted to embed physical laws and insights into the formulation of deep learning-based material models to increase the generalizability and stability of the solutions. The previously mentioned PINN architecture is one of methods in this category. Masi et al. [176] proposed a customized neural network architecture that imposes thermodynamics conservation law over its predictions. Their network structure (depicted in Fig. 5) primarily outputs free energy and later computes stress increment and dissipation rate through differentiation. By careful selection of activation functions over energy output and regularizing it according to the second thermodynamics law, the network predictions uphold thermodynamic laws by construction. This method is demonstrated for two material types of hyper- and hypo-elastic in an implicit macro-scale

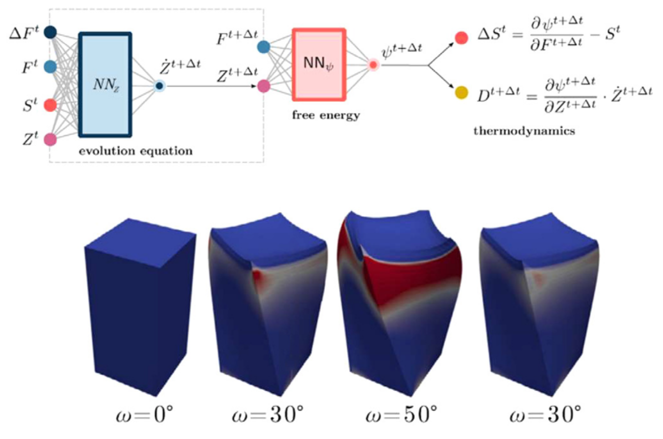

Fig. 5. Thermodynamics-based neural network for predicting plasticity. The architecture of the network (top) and an illustrative result (bottom) are shown [175].

solver. Further, this methodology is extended to capture microstructure variations using an autoencoder extension [175] (see Fig. 5) and within a recurrent neural network (RNN) formulation [103]. Linearized Minimal State Cell (LMSC) [26,27] introduced an alternative form of RNN formulation that is approximately self-consistent, i.e., the response does not depend on the increment size. While LMSC is less representative compared to its purely data-driven alternative, such as GRU, its self-consistency alleviates stability issues when used in an explicit solver. This method's weaknesses include requiring unintuitive initialization (hints at the sensitivity of the approach) and the lack of methodology for selecting stable increment sizes (unlike conventional FEM where one can compute the critical time step).

Another intriguing approach to embedding physics into data-driven material modeling is proposed in [268]. Xu et al. designed a neural network architecture (named SPD-NN) in which instead of predicting stress directly, only non-zero elements in the Cholesky matrix are predicted, and later stress tensor increment is derived from the Cholesky matrix. Using this construct, the tangent stiffness matrix remains symmetric positive definite (SPD) and; hence, creates a convex strain-energy field and satisfies the work criterion, which is shown to benefit the generalization and stability of the numerical simulations.

Besides incorporating physics at the modeling stage, physical principles can also be considered at the data pre-processing state. In a study on hot-rolled Ti micro-alloyed steel samples, Cui et al. [48] transformed their high dimensional steel composition and rolling parameters data with physical metallurgical principles and achieved a better performance in predicting yield strength and elongation when compared with using input data extracted from pure dimension reduction algorithms like an autoencoder.

As one can see, there are several options for which physical concept to select and how to implement it into deep neural networks (e.g., start from thermodynamics laws, plasticity concepts, or numerical self-consistency). While these methods show significant improvement over pure data-driven methods, they come with their unique limitations. The assumptions used in deriving the thermodynamics laws require considerable knowledge about the material as this information is used for deriving energy formulation and limits the materials that the model can be applied to. For instance, a common assumption is the strain-rate independency, which can be easily violated. Additionally, as these methods often use second-order derivatives, careful design of loss functions and activation functions are required to avoid sensitivity to noise and second-order vanishing gradients. Finally, these methods are mainly demonstrated for cases where they are subject to relatively simpler loading conditions and hardening laws and further investigations can shed light on the full extent of their capabilities.

A fundamental limitation of supervised training using conjugate stress-strain pairs is that it requires access to stress. While the strain can be directly measured using DIC, stresses need to be inferred given the external forces, except for the simplest of geometries. This motivates a different approach to data-driven modeling in which the material model is learned directly from strains and macro-scale external forces. The previously mentioned SDP-NN method achieved direct part-scale optimization by developing a finite element method framework that supports automatic differentiation [113,268]. Using their differentiable framework, the neural network was directly trained to infer stresses that lead to correct boundary forces. However, as reported by the authors, the optimization problem can only be solved given great initialization to stress distribution and might require starting from multiple initialization points to converge. Additional research has also shown promising results for capturing anisotropic behavior during cup drawing [71] and highly nonlinear behavior of material in high contact settings for both fluid and solid use cases [229,235].

3.1.3. Macro-scale regulated deep learning

Another approach to obtaining direct part-scale solutions is to introduce macro-scale physical laws (e.g., dynamic structural and deformation equations) as regularization terms into the optimization process of neural networks, which is broadly named as Physics-Informed Neural Networks (PINN). PINN is a promising method for building flexible learning models that easily incorporate heterogeneous data by adjusting the regularization terms in the loss function. For example, Liao et al. [158] proposed a hybrid physics-based data-driven thermal modelling approach of additive manufacturing processes with PINN and realized accurate temperature prediction and parameter identification. As another example of this methodology, Haghighat et al. [96] developed an approach that learns the material model directly from external forces under the assumption of linear elasticity, von Mises yield surface, and no hardening (see Fig. 6). They found that by embedding the physics the PINN model can accurately predict the solution for a wide range of parameters. This method was later extended to coupled damage elasto-plasticity, albeit in a case with a single element and von Mises plasticity assumption [95]. Recently, Niu et al. used the PINN framework to model multi-step loading and unloading cases [192]. Using comparable logic, Li et al. [153] proposed an equilibrium-based convolution neural network (ECNN) that predicts the spatial distribution of stress over the geometry and given external forces directly solves the global equilibrium problem. The loss function of ECNN consists of two components that are optimized simultaneously: the balance of internal nodal forces and the balance of external forces on the displacement boundary. The Deep Energy Method (DEM) method [190,226] offers an alternative formulation to classical PINN where by formulating the loss

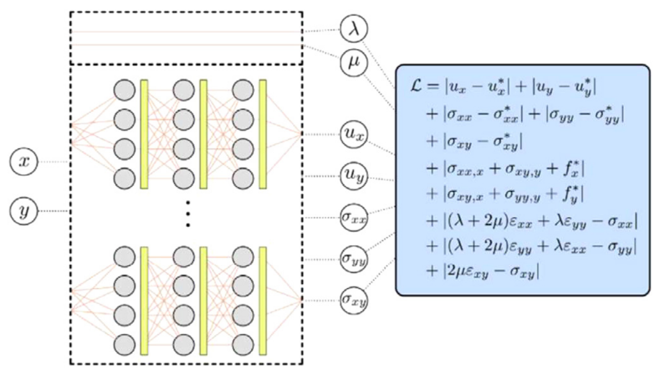

Fig. 6. Architecture of physics-informed neural network for material modeling where part-scale and dynamic structural equations are incorporated into the training process [96].

function in terms of energy, one can avoid the second-order differentiation of neural networks. Other notable examples of part-scale regularized deep learning are proposed for hyperelasticity [159], strain-rate and temperature dependence viscoplasticity [12], and elasto-plasticity [66]. Generalizing finite element method within deep learning framework, Saha et al. [223] proposed Hierarchical Deep-learning Neural Network (HiDeNN); the HiDeNN family of methods have demonstrated potential in solving various problems in computational mechanics, such as topology optimization [152], nonlinear problems [162], higher order analysis [201], etc.

The current drawback of part-scale regulated deep learning methods is that they are applied to relatively simple material models when a closed-form or well-defined PDE exists. Therefore, these methods are yet to be proven effective beyond parameter identification and interpolation over geometry. Additionally, these methods have shown to be sensitive to the type of elements (e.g., low-order elements) and struggle when dealing with discontinuous fields [82].

3.1.4. Sparse optimization

A fundamentally different approach to directly learning material models from part-scale data is to formulate the problem as a sparse optimization. By collecting a large collection of candidate material models, the sparse optimization algorithm attempts to find a minimal set of candidates that capture material behaviors. This is similar to the established literature on sparse system identification for dynamical systems [35]. A pioneering version of this idea for plasticity is proposed in [77], where they construct a library of material yield surface functions, represented using Fourier series. The optimization problem is solved using a nonlinear optimization with a sparsity promotion algorithm (trust-region reflective Newton solver) which leads to discovering yield surface characteristics, i.e., original yield surface shape and the hardening behavior (see Fig. 7). Note that due to the sparsity of optimization signal, this method puts significant assumptions on the material model, requiring a homogeneous and isotropic material for which linear elastic behavior is followed by associated, pressure-insensitive plastic behavior with isotropic and or kinematic hardening. It can be expected that in this approach, the model predicts very well when the candidate library is carefully designed and tuned. When the true yield surface is not within proximity of the provided candidates the optimization may fail. Similar results were reported in dynamical system applications using similar underlying optimization techniques [64].

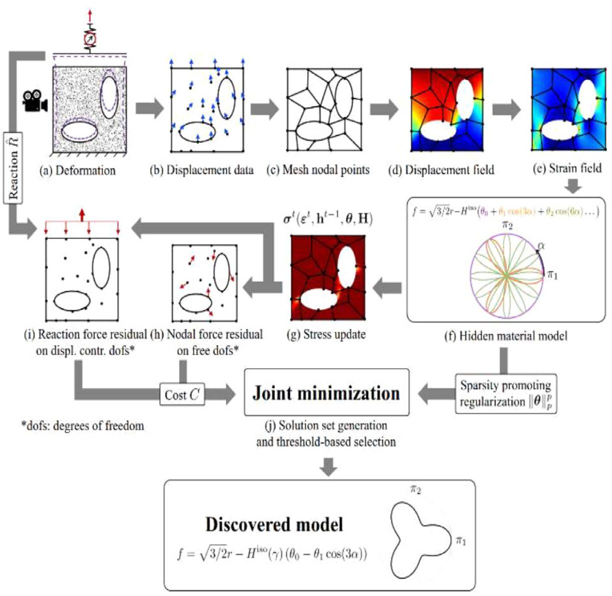

Fig. 7. Plasticity discovery using sparse identification from candidate yield surfaces [77].

3.2. AI for failure prediction

Failure in metal forming takes various forms, including necking and fracture, and buckling. Failure prediction using AI can take numerical data and/or experimental data. Below, past work related to failure prediction will be summarized.

3.2.1. Necking and fracture

Necking and fracture are common failure modes in metal forming processes, which can be effectively modeled and predicted with AI methods. Yao et al. [274] proposed a neural network based calibration method to accurately predict damage initiation, accumulation, and fracture of the 6061 aluminum alloy sheet specimen with displacement control boundary conditions. Through this work, a semi-coupled fracture model was developed and used to train a back propagated neural network. The experimental force-displacement curve was inputted into the ML model to obtain predicted results, this process is depicted in Fig. 8. A model for the evolution of ductile damage in terms of void fractions using fully connected neural networks (FCNN) and experimental data was proposed in Schowtjak et al. [233]. They showed the potential of using the data-driven model obtained from pure experimental notched tensile tests and in-plane torsion tests for accurate predictions of damage evolution in air bending. However, less accurate results were obtained for Radial Stress Superposed (RSS) bending as the loading states in RSS bending were outside of the domain of the training data.

Jaremenko et al. [122] studied the growth behavior and traceability of the necking area using a weakly supervised ML approach with

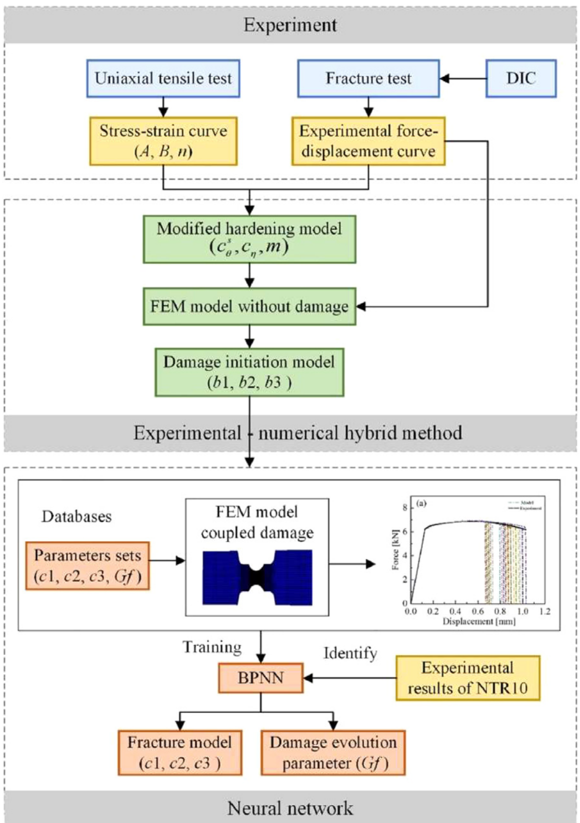

Fig. 8. Process for parameter identification method using a back propagation neural network for machine learning assistance [274].

data obtained from a Nakajima test. Liu et al. [161] used supervised machine learning to quantify the bendability and resistance to fracture of steels considering the effect of subsurface non-metallic inclusions, where they consider inclusion size, location and strength as the input space while the macroscopic flexural strain to failure as the output prediction. Chen et al. [42] studied tearing failure in cold rolling process and used several classic ML methods such as random forest and naïve Bayes to reveal a functional relationship between input variables obtained from domain experts (e.g., rolling speed and pressure feedback) and output tearing event. Sun et al. [246] used a neural network approach for the determination of ductile fracture properties of 16MND5 bainitic forging steel, where the nonlinear relationship between geometric sizes of the specimen (input) and the coefficients for the J-integral vs. crack growth resistance curve (output) was well learned. Pandya et al. [200] proposed an isotropic neural network based fracture initiation model to predict the onset of fracture for aluminum alloy 7075 manufactured through a hot stamping process. Li et al. [156] used stress state, strain rate and temperature to predict the onset of ductile fracture for an aluminum alloy AA7075-T6.

In the context of failure prognosis and process supervision, Di Lorenzo et al. [57] used NNs for a fracture forecast in an upsetting process. The network was trained with experimental data of different forming processes except of the upsetting process. In this context Klocke and Breuer [137] used the fracture generating forming histories for the training of an artificial neural network. With this ANN a better failure prognosis in different forming operations for example upsetting or blanking could be achieved.

In sheet metal forming, several works have focused on predicting the forming limit diagram (FLD) with ML methods. Jaremenko et al. [123] adopted a CNN as feature extractors and used Student's t mixture model to cluster the learned features so that the brittle regime of a FLD is better addressed; in another similar work of theirs [5], a pattern recognition based method was employed for the determination of the FLD defined by the onset of necking. Chheda et al. [46] constructed a two-stage ML approach with support vector regression and gradient boost regression so that the trained ML model successfully predicted FLDs with R^2 value above 0.93. This ML approach was used to predict the simulations results of a cross-die geometry as seen in Fig. 9**.** Yatkin and Korgesaar [275] used a 1D-CNN to predict sheet strain localization of sheet metal forming.

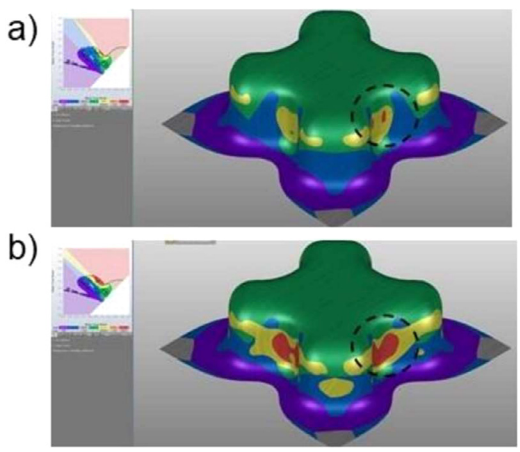

Fig. 9. Simulation results for stamping process using (a) measured and (b) predicted values for the forming limit diagram. Predicted results were obtained using a two-stage trained machine learning model [46].

3.2.2. Buckling

Buckling is a type of instability that occurs when the energy attributed to the compressive stresses in the part exceeds the deformation energy attributed to a buckling mode in the part, leading to failures of undesirable part geometry. Buckling analysis is typically performed with nonlinear finite element methods that are computationally expensive, hence data-driven surrogate models are of particular interest and importance. Direct predictions of buckling occurrence with ML-based methods have been an active topic in recent years. Ly et al. [169] developed a hybrid model combining several ML algorithms for predicting the critical buckling load of I-shaped cellular beams with complex internal structure. Duong [62] used a fully connected neural network (FCNN) and successfully assessed the critical buckling load of a functionally graded plate. As a notable factor, buckling with imperfections was paid special attention to in several works. Zhu et al. [286] investigated buckling of imperfect reticulated shell with neural networks and support vector regression. Wagner et al. [262] applied decision tree-based ML methods to derive general design recommendations for a maximum buckling load and a minimum imperfection sensitivity for laminate stacking of composite cylinders. ML for thermally affected buckling were studied in [10] for graphene oxide reinforced nanocomposites and in [189] for ballasted railway tracks. Other than end-to-end buckling predictions, Zhuang et al. [288] proposed a deep autoencoder energy method (DAEM) for modeling and solving buckling behavior of Kirchhoff plates; their approach is similarly to the concept in PINN family and is further accelerated with transfer learning. The proposed DAEM, shown in Fig. 10, has the total potential energy equation expressed in the autoencoder. The approach was demonstrated effective in predicting relatively simple buckling cases.

Beyond forward prediction, Maurizi et al. [177] tackled the more challenging inverse design problems of buckling; they combined deep neural network and genetic algorithm so that truss lattice materials with superior buckling resistance were rationally designed. In [54], the effectiveness of a neural network for predicting wrinkling limits in sheet metal-forming was examined; it was found that the trained neural network is capable of covering a wide range of material properties and its prediction of nominal strain at the onset of wrinkling is in reasonable agreement with the analytical results. In [202], neural networks and genetic algorithm are combined to optimize the bending sequence in roll forming, so that the longitudinal strain is maintained to be less than the buckling limit to avoid failure.

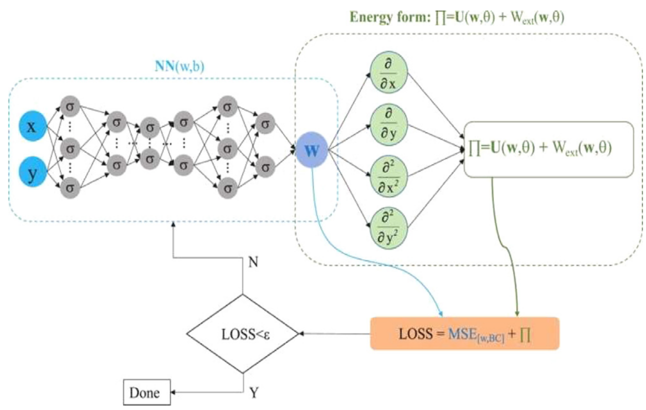

Fig. 10. Framework of deep autoencoder energy model used to predict bending, vibration, and buckling behavior of Kirchhoff plates [288].

3.3. AI for interface and process modeling

An important aspect in metal forming is the understanding of the wear behaviour of the tools. Gouarir [90] used machine learning techniques for a better in-process tool wear analysis. The experimental results indicated that a conventional neural network (CNN) approach is suitable for the identification of the existing correlation between the forces produced during the process and the wear. An artificial-neural-networks-based in-process tool wear prediction system was presented by Chen and Chen [39]. Their system was able to correctly predict the occurring tool wear. A more generalized study was

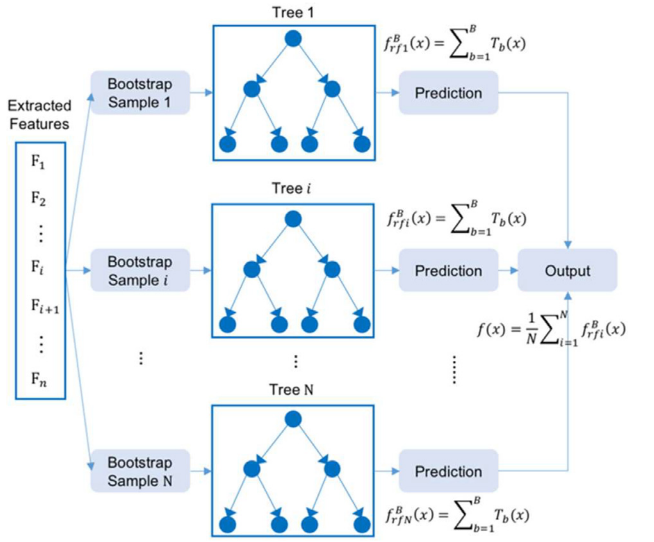

Fig. 11. Schematic of random forest architecture used to predict tool wear using regression trees [266].

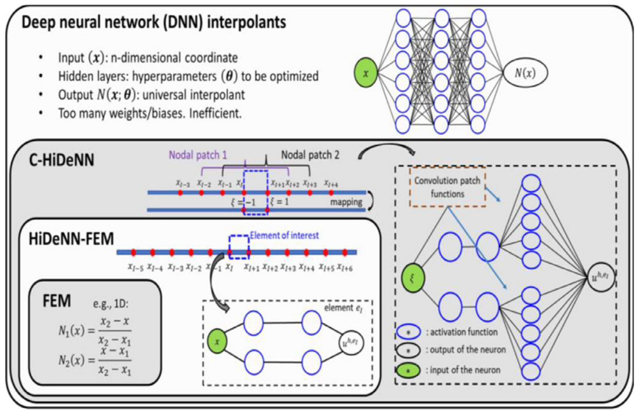

Fig. 12. Diagram of interpolation spaces. Elementwise HiDeNN-FEM shape function has partially connected two hidden layers while that of C-HiDeNN has one additional layer that represents convolution patch functions. DNN interpolants are constructed with fully connected feedforward neural networks [223].

presented by Wu et al. [266]. Their comparative study was focused on machine learning algorithms. They compared an artificial neural network (ANN) with support vector regression (SVR) and a RF-based prognostic method for the tool wear. They demonstrated that the predictive model trained by random forests can predict tool wear very accurately with the architecture demonstrated in Fig. 11.

Petkar et al. [206] used an ANN with differential evolution optimization algorithm to analyze a cold forging backward extrusion process and enhance the lifetime of the punch by optimizing various parameters like billet size and punch angle on the basis of the identified forming responses such as effective stresses and forming forces. The findings of Kubik et al. [141] reindicated that a regressive ML model can accurately predict abrasive wear levels on sheet metal forming tools in real-time. The study focused on two sheet metal forming processes, blanking and roll forming, which exhibit distinct time series characteristics. Despite these differences, the model successfully estimated the cutting-edge radii and roll-edge radii on the forming tools by following the systematic approach of the Knowledge Discovery in Time series and image data in Engineering Applications.

Finite element simulations are a widely used numerical method for solving partial differential equations (PDEs) that describe the above-mentioned behaviors. These simulations are based on discretizing the workpiece into a mesh of finite elements, which reduces the problem from solving an infinite dimensional PDE to algebraic equations with finite degrees of freedom. There are mainly PDEs resulting from the mechanical and thermal governing equations in metal forming processes. Hence, finite element simulations require a detailed understanding of the underlying physical laws and mechanisms that govern the behavior of the material, the interface and the system, which can be computationally expensive due to fine mesh and small time-step used for resolving complex behaviors like plasticity and crack propagation, and the underlying physics may not always be fully understood, such as interface behavior between tool and workpiece. For example, a single three-path English wheeling simulation using commercial software might take more than one day to obtain reasonable predictions of local deformation while the experiment can be performed in seconds. Similar challenges exist in simulating incremental forming processes or stamping of bipolar plates ($>$ 100 mm x 100 mm) with local fine features in the micrometer scale. This multi-scale nature can limit FEM's practical usage for large-scale problems.

Aiming to overcome the difficulties that FEM faces, machine learning approaches have been explored to replace FEM simulations to provide a system-level model in addition to that for constitutive models described in Section 3.1. Since research in this field requires significant involvement of software engineering for developing new architectures, which is out of scope for metal forming researchers and practitioners, two examples (one in solid and one in fluids domain) will be briefly illustrated so that readers are aware of developments in computational mechanics. Saha et al. [223], as shown in Fig. 12, proposed a less-densely connected NN as a kernel function, which can be tuned to have superior accuracy, higher smoothness and fast convergence rates compared to the shape function used in the traditional FEM approach. For reaching a H^1 norm error of 10^{-3} in a 2-D Poisson's problem, they demonstrated a 10^6 speed up compared to the linear FEM model and 10^4 speed up compared to the cubic FEM model. In computational fluid dynamics area, White et al. [264] reformulated the simulation problem to effectively increase the size of constrained pre-computed datasets and introduced a new NN architecture (called a cluster network) with an inductive bias. They showed that their approach is nearly as accurate, however, an order of magnitude faster.

In metal forming, Petrik et al. [207] proposed a fast surrogate model called CrystalMind for open die forging based on PointNET++, which is an AI architecture that works on point clouds and considers local and global features. As shown in Fig. 13, CrystalMind predicts the full deformation field in the workpiece including microstructure resulting from a forging stroke in milliseconds with an accuracy close to the underlying FEM training data and hence allows for schedule planning using optimization techniques, see Section 4.3.

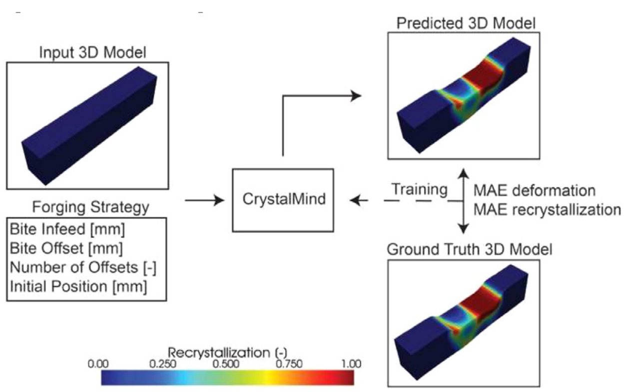

Fig. 13. Working principle of CrystalMind [207]. It predicts deformation and recrystallization as a consequence of flat forging strokes which can be placed with a range of bite infeed and offset values.

3.4. Summary for AI in process modeling

Forming is a multi-physics multi-scale manufacturing process that has been traditionally modelled using analytical estimation or finite element methods. The choice between using a machine learning approach or a finite element simulation will depend on the specific needs and goals of the application. Finite element simulations may be more suitable for problems where a more detailed and accurate representation of the behavior of materials is needed, or where the mathematical models used are well-established, and material data are readily available. Machine learning approaches may be more suitable for problems where large amounts of data are available, or where the underlying physical mechanisms are not well understood, or the computational cost in physics-based model is overwhelmingly unpractical. Machine learning techniques may offer some advantages over finite element simulations, including increased efficiency and the ability to incorporate additional data into the model.

The most advancement made using AI in metal forming process simulation is in the area of material constitutive modelling. AI algorithms are not restricted to specific functional approximation spaces and can hence model any material behavior. They have the potential to replace the plethora of models used to describe the yield locus or hardening by a unified approach as described in Section 3.1.

The adoption of ML-based or hybrid approach in industrial forming simulation has been slow, probably due to the facts that codes and datasets are not readily available for many materials or extremely expensive to obtain, such as residual stress distributions as a result of metal forming operation. Hence, it is difficult to calibrate complex models. Villarreal et al. [259] introduced a deep reinforcement learning algorithm for design of experiments that maximizes the information gain measured by Kullback–Leibler divergence obtained via the Kalman filter (KF), suitable for the high-dimensional parametric design space. Experiments were formulated as a decision tree and a Bayesian update of the parameters was used to enhance the state representation. Such approach can be used for effective parameter identification in numerical models and for efficient design.

4. Designing parts, tools and processes using AI

Since the 1990s, AI techniques have found application in a range of design tasks within the domain of metal forming. While so far only Hamouche and Loukaides [97] have explored the capabilities of machine learning in classifying and selecting sheet forming processes, the majority of research in this area has concentrated on leveraging AI for optimizing process parameters (Section 4.1), tool and preform design (Section 4.2), and process planning (Section 4.3). The following sections provide a comprehensive review of prior work in this field and offer an analysis of the prospective applications of AI in the future.

4.1. AI for process parameter design

A recent review by Campos et al. [11] shows that a wide variety of optimization algorithms has been applied in metal forming, and that a number of publications have used meta-modelling techniques to reduce the computational effort involved in computing the cost function [101]. Meta-models are crafted to replicate the behaviour of a more intricate model while reducing computational expenses, typically relying on spatial interpolation methods like kriging. An evident use of AI algorithms is to substitute these meta-models.

Regarding the prognosis of springback in a bending process, Narayanasamy and Padmanabhan [185] compared a regression model to an ANN. The neural network led to an improved prediction of the springback behavior after bending showing the potential of AI for the improved process prediction. In [19], Baseri et al. compared a back propagating neural network (BPNN) with a varying number of layers and nodes as described in [51] to a radial basis function neural network (RBFNN) with three layers and a varying number of nodes as proposed in [33]. Note that both BPNN and RBFNN belong to the category of FCNN as described in Section 2 (Fig. 2a). The main difference is the selection of their activation function used, sigmoid function and the radial basis function for BPNN and RBFNN, respectively. A better prediction of the bending angle was achieved with the BPNN. Decisive factors for the quality of the predictions made by neural networks are the number of layers and of the nodes. Froitzheim et al. [81] utilized an ANN to model a ship panel sheet forming process, replacing the traditional manual approach. The ANN facilitated accurate and automated predictions of process results and parameters, addressing the limitations of numerical simulations in providing predictions in real-time. Similar usage of AI for the optimization of process parameters is exemplified by Zhou and Cheng [285] for deep drawing and by Sbayti et al. [231] for incremental forming. Römisch et al. [215] Klicken oder tippen Sie hier, um Text einzugeben.demonstrated the value of data-driven methods in analyzing process parameters for cold forward extrusion of metallic pin structures used in joining operations. They used experimental data and machine learning techniques to create a metamodel for identifying key factors in the extrusion process. Additionally, the authors suggested extending the data-driven approach to a broader process chain, including joining and joint characterization, to enhance its versatility. There are a number of papers in which AI algorithms are primarily used as regressors and combined with optimization methods. Lu et al. [166] used a random forest (RF) approach to predict the outcome of a stretch bending operation and combined it with multi-objective optimization to identify optimal forming paths. Kurra et al. [146] applied ANN, Support Vector Regression (SVR) and Genetic Programming (GP) to minimize surface roughness in single point incremental forming (SPIF). Mearyo et al. [179] optimized the ANN topology to predict mechanical properties of wrought aluminium alloys, and found that more than 150 perceptrons are needed in the hidden layers. Tang and Chen [248] used an SVM capable of accounting for nonlinearities in pattern recognition and regression to model part quality in stamping as a function of process parameters. Their approach adopted adaptive importance sampling techniques, which allowed them to account for uncertainties, opening the way for robust design of cup-drawing experiments. Machine learning algorithms, such as decision tree regression, random forest, support vector, were applied in [25] to optimize the friction riveting process. The results showed that considering process parameters and mechanical energy input to train the machine learning algorithms is useful for the prediction quality of the mechanical properties.

The temperature field is a crucial factor in numerous metal forming processes. Elevated temperatures generally reduce forming force and improve material formability, yet they also pose challenges such as increased tool adhesion, decreased tool strength, complex microstructure changes, and thermal distortion due to uneven temperature distribution. Consequently, the capability to predict and measure both local and global temperature fields is highly sought after for effective process design and monitoring. Since physics-based fully coupled thermal-mechanical simulations can be computationally expensive for process design, Jiang et al. [126] developed a CNN to predict the forming temperature at the tool/sheet interface in an electrically-assisted double-sided incremental forming. To enhance computational efficiency in generating synthetic data, a CNN model was trained using temperature outputs from a simplified FEM model. This study underscored the importance of justifying these model simplifications, emphasizing that domain experts with a strong grasp of the underlying physics and validated experimental data should be involved in this process. King et al. [134] developed a physics-informed machine learning (PINN) model that predicted heat

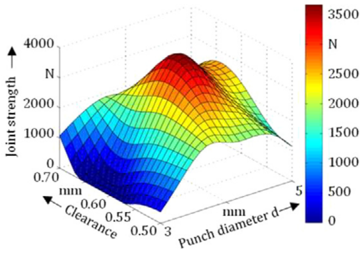

Fig. 14. Result of a process map from an expert system trained on simulation data [147].

generation in shear assisted extrusion. The model has qualitative agreement with crystal plasticity simulations and can be used in process design.

The conventional design processes, based on expert knowledge, can be slow and error-prone. To overcome these challenges, a toolbox of artificial intelligence methods has been developed [65]. This toolbox includes various techniques and enables the prediction of joining technologies, locations, and dimensioning while considering complexity and cost, aiming to meet the needs of a diverse range of products.

Machine learning algorithms have been applied also to investigate specific target variables, such as load-bearing capacities in clinched joints. Lambiase and Di Ilio [147] optimized clinching tools with extensible dies to enhance the strength of clinched joints across various sheet thicknesses. They used an expert system trained on finite element simulation data, coupled with a genetic algorithm for optimization. This versatile expert system can be repurposed for different objectives, eliminating the need for additional simulations. Fig. 14 illustrates the relationship between clearance, punch diameter, and joint strength as an example.

While the list of published papers is not exhaustive, it shows that machine learning is predominantly used to build regressors that can be evaluated faster than full-scale process models. However, using ANN to model a system to be optimized with a gradient-based optimizer requires to pay attention to the following issues:

- Differentiability: For the optimization algorithm to work, the cost function and the ANN model must be differentiable. This means that the model must be composed of differentiable functions, such as sigmoid or ReLU, and not use any non-differentiable operations such as max or step functions.
- Extrapolation: ANNs are typically trained on a limited range of input data, and their ability to make accurate predictions outside of this range is uncertain. Meta-modeling and kriging are specifically designed for extrapolation, as they are based on approximating the underlying model over a limited range of inputs.
- Overfitting: Overfitting occurs when the ANN model is too complex or the data is too few so that the model fits the noise in the data rather than the underlying signal. This can lead to poor generalization and poor performance on unseen data, affecting the optimization process.

Given that multiple prior studies used meta-models (see e.g. [28]) with a sound mathematical foundation for optimization of metal forming processes, work that uses machine learning lacks mathematical rigor. Future work in this domain must make sure to use techniques such as regularization and cross-validation to prevent overfitting, and Bayesian optimization or population-based methods to explore the cost function more efficiently.

While most of the work reviewed so far combines ML-based surrogate models trained by supervised learning with gradient-based or heuristic optimizers, RL algorithms are only being taken up slowly. Jeong et al. [124] used compression tests on AISI 4340 alloy at 900–1200 °C to set up a processing map and used a Q-learning based RL algorithm to optimize forming parameters, thus preventing defects. Stendal et al. [244] applied RL to find optimal ram trajectories for isothermal forging of rather titanium aluminides which are known for their limited ductility. At the moment, there is no in-depth analysis of the performance of RL compared to more conventional optimizers.

Another promising line of research could be to use differentiable simulators (DS) as system models, which have been applied in a variety of areas such as fluid mechanics [23], finite element solvers [269], molecular dynamics [23], robotics [105] and additive manufacturing [183]. DS can be used to simulate physical systems and are differentiable with respect to their input variables, e.g., process parameters that dominate the behaviour of the system. With the derivative computed by the automatic differentiation technique, efficient gradient-based optimization algorithms can be used to optimize over model parameters and achieve higher performance requirement.

A less common approach to using AI for process optimization is to invert process models for metal forming using machine learning algorithms to learn the relationship between the input parameters and the output of the process. In early work by Ruffini and Cao [216], a fully connected neural network was used to identify when and by how much a stepped binder force should be applied to obtain a targeted and consistent springback angle in a channel forming at the presences of variations and uncertainties in materials and lubrication conditions. Frayman et al. [79] developed a neural network based inverse model of a sheet forming process which outperformed a linear model in finding appropriate input parameters. Recently, Ryser et al. [220] trained data-driven models on datasets consisting of pairs of input and output data (draw-ins) from a stamping process simulation. The trained model predicted the output of the process for a given set of input parameters, allowing the input parameters to be adjusted to achieve the desired output. Later, the approach was extended to experimental work by determining the position of markers on the sheet surface [219]. Another notable study is the one conducted by Yuan et al. [277], where inverse modeling is achieved through the training of a random forest model. This model predicts the initial texture and constitutive model parameters based on inputs such as a stress-strain curve, loading conditions, and final texture. Notably, this approach permits both forward and reverse machine learning configurations, as illustrated in Fig. 15. Given that inversion of process models in general offers new ways of solving ill-posed optimization problems, as showcased e.g. in the inversion of structure-property relationships of metamaterials [20], future work on data-driven inverse models could outperform classical optimization approaches.

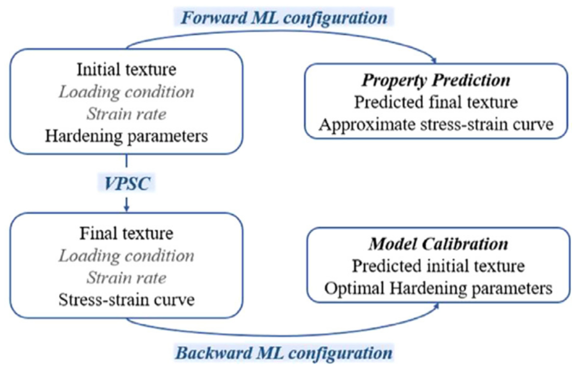

Fig. 15. Training configurations of property prediction (forward) and model calibration (inverse), according to [277]. VPSC stands for Visco-Plastic Self-Consistent code.

4.2. AI for tool and preform design

AI techniques such as expert systems and evolutionary programming can be applied to tool design problems. Expert systems were a popular AI technique in the 1980s and 1990s. Already in 1991, Sitaraman et al. [240] proposed a knowledge-based system for the design of a stamping process sequences, claiming to have achieved a 90% reduction in design time compared to conventional design methods. In the same year, Pillinger et al. [209] presented a system for the design of forging tools programmed in the Lisp programming language. The work discusses improving design processes by integrating an intelligent system that combines rule-based design with simulation. The design rules, however, were fixed, leading to repeated issues in die designs. While the system was able to identify and suggest improvements, a faster approach reportedly involved manually updating design rules based on system insights. [251] put forward a knowledge-based system for the design of process plans for sheet metal designs, claiming that this system was successfully implemented in the industry. Similarly, [239] implemented a knowledge-based process layout system using decision tables for deep-drawing of axisymmetric parts. In 1998, a knowledge-based design tool for progressive dies for the manufacture of small metal-stampings for electrical and electronic equipment was described, but it remains unclear from the work whether the approach received industrial take up [45,132], and claimed to offer comprehensive support in die design. From today's perspective, it is difficult to assess how advanced these expert systems were and how well they generalized and offered industrially useful solutions for die design. It is clear from the literature that the popularity of expert systems diminished in the late 1990s. Probably, the substantial manual effort required for setting up and maintaining their knowledge base and their limitations in adapting to new situations were the major obstacles to a broader industrial take up. After the decline of research into expert systems, machine learning algorithms gained popularity due to their ability to learn from data and adapt to changing circumstances. [208] resented a hybrid intelligent systems approach for die design for sheet metal parts that combined a knowledge-based system with FEA and ANN. It was claimed to support conceptual design, rapid prototyping, automatic evaluation, optimization of new designs, and process optimization, with self-learning capabilities. The system automates input adjustments regarding process, material, and geometry to enhance manufacturability. Case studies demonstrate its ability to optimize design by automatically adjusting variables like punch velocity, drawbead force, blankholder pressure, and material properties to eliminate forming defects. The original part geometry and the subsequent optimized geometries are Fig. 16. In later work, ANN fully replaced expert systems. [257] proposed an ANN-based algorithm to optimize the tool shape for reducing springback in sheet metal stamping. They put forward a new methodology for die optimization to address springback in automotive manufacturing. The method utilizes a curvature adjustment approach and FEA calibration to improve the precision and efficiency of die design, but showcase it only on a single part geometry. The approach presented by Fritzsche et al. in [80] was related to the clamping systems for the fixture of car-body panels in joining operations, which normally have to be exchanged for the production of different car models. By correcting the positioning depending on the different external loads using a database system based on AI, the joining fixture parameters are adapted automatically, which makes it possible to reuse the main part of the body shop production equipment for positioning and clamping the parts for various car models [80]. An image-based surrogate model using a U-net convolutional neural network (CNN) with an attention-based ResNet layer was developed by Liu et al. [163] to improve prediction of shape errors in asymmetric channels in the automotive industry. Traditional models struggle with accuracy because they cannot incorporate location information. The proposed model, enhanced by automatic data preprocessing that converts information into image data, accurately predicts dimensional deviations in real-time. An optimization framework combining this CNN model with a differential evolution algorithm significantly enhances forming accuracy, confirmed by validation experiments.

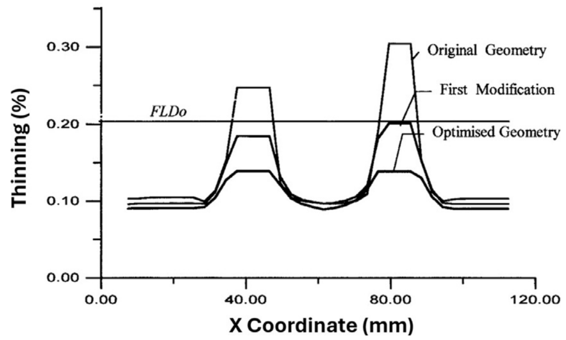

Fig. 16. Application of hybrid intelligent system combining knowledge-systems with FEA and ANN according to [208]. This combination enables design iteration optimization of strain distribution of commercial quality steel to be within the material's limit strain of 0.20%.

Despite this reported success it is difficult to assess both the academic and industrial merit of these AI approaches, which would only be possible had these methods been tested with the same set of representative geometries.

AI was also applied in die design for bulk forming. [44] applied a Radial Basis Function (RBF) neural network and a back propagation neural network to forging die design and concluded that both networks performed well "as long as the number of learning samples is enough" [279]. report that porthole die design can be accelerated using a Support Vector Machine Polynomial Kernel (SVMP) model. The main conclusion was that the SVMP model demonstrated the highest performance for each output variable, but the paper does not show whether the method generalizes. Porthole die design was also tackled [276]. The primary objective was to achieve a balanced flow within the die, taking into account parameters such as the number of portholes, their shapes, arrangement, distribution, and die bearing. The study introduced two distinct DCNN architectures, one for the classification of porthole geometry and another for the detection of factors related to die bearing design. Training the porthole model yielded varying levels of accuracy for different attributes: 50% for porthole number, 80% for arrangement, 14.29% for shape, and 66.67% for distribution concerning the extruded profile, highlighting the need for further research in this field.

In parallel to tool design, AI-based pre-form design has been investigated. Kim and Kim [133] presented a neural network based approach to initial billet design in forging, reducing the number of finite element simulation for designing the die for a rib-web part, i.e. well defined geometry. Chan et al. [37] developed a hybrid approach combining FEA and ANN to find optimal design parameters for an axisymmetric forging, which limits the range of geometries that the algorithm can handle. Similarly, ANN were used to design an optimal preform for a cold heading process, leveraging formability and forming forces [138]. In these works, rather simple neural networks are used as regressors. A novel platform for addressing shape distortion in sheet metal stamping using deep learning to inform tool compensation was put forward by Attar et al. [14]. The platform iteratively updates tool geometries to counteract springback while satisfying thinning criteria, akin to GANs but with a classical optimization approach. Fig. 17 shows the deep learning-enabled tool compensation process.

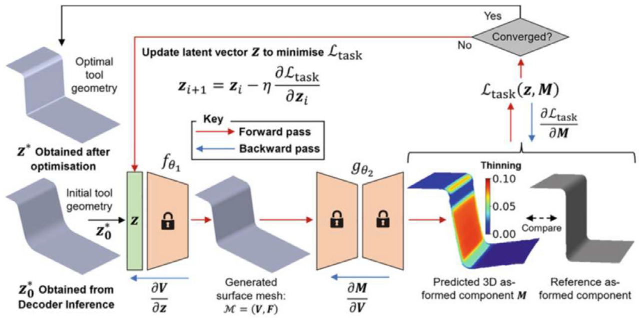

Fig. 17. AI-based tool compensation to reduce springback in bending [14].

An automated data preprocessing method that converts design parameters and simulation results into image data for asymmetrical channel chain-die forming was introduced by Liu et al. [163]. They utilized a U-net CNN to establish an image-based surrogate model for predicting dimensional deviations across the formed part. To enhance network sensitivity to different regions of the die surface in sheet metal forming, they proposed an attention-based ResNet layer, which replaced the bottleneck of the U-net-style base network. This approach led to a significant improvement in forming accuracy. Another machine learning approach for optimizing blank designs in deep drawing was introduced by Lee et al. [150], using a Blank Design Mapping Function (BDMF) that combines Gaussian Process Regression with a Radial Basis Function kernel. Their method correlates predictions with their uncertainties, trained on data from a 3D finite element analysis model. Validated by laboratory experiments on steel and aluminum, the method showed maximum deviations of 13.3% in drawing force and 0.35% in earing profile. The BDMF's predictions for metal blanks were highly accurate, with deviations of 1.3% in thickness and 0.25% in outer radius, proving its reliability and generality across different flanged geometries.

In the work surveyed above, neural networks are used for setting up a mapping with design parameters as inputs and design criteria as outputs, allowing to optimize designs. This task is similar to finding optimal process parameters discussed in the previous subsection (Section 4.1), and hence, the challenges and recommendations made there also apply to die and pre-form design.

More advanced AI methods can be found in recent work on generative design (GD), i.e., the use of computational tools to automatically generate design solutions that meet specific requirements or constraints. Oh et al. [193] proposed a combination of topology optimization and generative adversarial networks (GANs) to create a large number of designs as shown in Fig. 18 based on limited data sets. An adaptive ANN-based generative design approach has been proposed and developed for layout design. Qian et al. [211] combined GANs with CNN and a genetic algorithm to optimize a heat transfer problem. In contrast to the work on tools and pre-form design in metal forming, AI-supported generative design algorithms allow to generalize and explore new designs by the use of GANs.

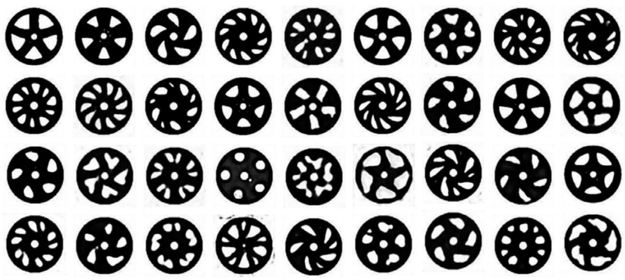

Fig. 18. Images of generated wheel designs created using the Boundary Equilibrium Generative Adversarial Network (BEGAN) according to [193].

4.3. AI for planning problems in metal forming

Various metal forming processes are multi-stage processes. Naturally, processes like breakdown rolling of cast blocks or open die forging require multiple stages. Planning of such processes can be interpreted as a sequence of discrete decisions. In sheet forming, Garcia et al. [83] addressed the bending tool repositioning problem which belongs to the class of NP-hard problems with two algorithms: a two-step heuristic and an approximated mixed-integer linear programming (MILP) heuristic. The MILP heuristic performed best, minimizing repositioning and reshuffled segments. The MILP model's computational demand was found to be high for large instances, though such instances are rare in industrial settings. This work does not exploit AI for discrete optimization problems, which is a vivid research area in other fields such as path planning in additive manufacturing, where e.g. Monte Carlo Tree Search (MCTS) algorithms have been used recently to optimize deposition paths [237]. Hartmann et al. [99] introduce an automated approach for generating tool paths in incremental sheet metal free-forming processes, using an artificial neural network architecture to produce parts directly from digital models. The study focuses on designing an effective network input and output structure, generating balanced datasets for training, and evaluating different training algorithms and network configurations. The system's effectiveness is validated through automated production of sheet parts, showcasing the potential and limitations of the proposed manufacturing system. Sala et al. [224] present a planning algorithm for Laser Peen Forming (LPF), aiming at precise bending of sheet metals. A data-driven approach, specifically an Artificial Neural Network (ANN), was developed to predict deformations from LPF under different conditions. The ANN's predictions facilitate a novel process planning method, enabling desired deformations in thin Ti-6Al-4 V sheets, demonstrated through one-directional, bi-directional, and pre-bent specimen deformation adjustments. For incremental forming using a moving heat source a novel prediction method that integrates an Improved Salp Swarm Algorithm (ISSA) with an Extreme Learning Machine (ELM) was introduced by Li et al. [154] to enhance line heating and forming processes. Initially, the method uses a three-dimensional FE simulation to analyze how process parameters affect deformation. It then employs the ELM network, trained with simulation data, to predict hull plate deformation. The ISSA is developed to optimize the ELM's input weights and hidden layer biases, thereby stabilizing prediction outcomes. Comparative analysis shows the ISSA-ELM model outperforms other models in predicting line heating and forming effects.

As mentioned in Section 3.3, Petrik et al. [207] proposed a fast surrogate model for open die forging based on PointNET++, which is able to predict the full deformation field of the workpiece including microstructure in milliseconds and hence allows for schedule planning . This work shows that AI models are important for generating large training sets, which are required for advanced planning and scheduling algorithms such as RL and MCTS.

First attempts of using AI algorithms such as RL in forming schedule planning were reported for hot stamping, where RL was showcased to outperform an industrial controller for the cycle time [191]. While the number of control parameters is rather low in this work, more complex scenarios are found in bulk forming. In hot rolling, reinforcement learning was successfully applied by Idzik et al. [118]. They utilized RL and analytical rolling models for pass schedules planning in rolling processes and ensured consistent product quality. The Deep Deterministic Policy Gradient algorithm automates pass schedule design, combining established rules with new strategies to maximize mechanical properties. This approach was validated using a laboratory rolling mill and allowed for adaptive scheduling to manage process disruptions efficiently and reduce material waste. Dornheim et al. [59] compared two deep RL algorithms for optimizing processing paths based on structure space representations and objective functions. Single-goal structure-guided processing path optimization combines function-based reinforcement learning with reward shaping for guided optimization. Multi-equivalent-goal structure-guided processing path optimization extends this to handle multiple equivalent target structures efficiently. It is shown that complex tasks such as the optimization of crystallographic texture can be performed using these RL approaches. Further research into using RL for process planning and scheduling is needed to understand the full potential and limitations of the approach.

4.4. Summary

Rather standard machine learning approaches have been applied to design of process parameters, die and preform design problems in metal forming so far. Mostly, machine learning is used to build regressors replacing the underlying more costly process model. More advanced AI techniques such as optimization based on differentiable simulations and AI-supported generative design algorithms have not yet found their way into design problems in metal forming and offer untapped potential to significantly improve the efficiency and effectiveness of the design process including the design of forming processes and tools for metal forming. Additionally, the coupling of isogeometric representation in the classical work of Hughes et al. [116] on modeling complex topology with deep learning, represented by and Gasick and Qian in a recent work [84] provides great potential in rapid and effective design of preform, tools and processes. Only very recently, advanced planning algorithms such as RL have been explored in metal forming, and there are various options for future research into planning complex multi-stage forming processes using RL as well as high-performance heuristic search algorithms such as MCTS. A striking point is that the relevant work shows a large variety of used methods which are applied to different processes and part geometries. This makes a direct comparison of the different approaches impossible, and shows that the forming community should establish a set of benchmark parts to compare the performance of existing and future algorithms.

5. AI for process control

Process control must have an objective function consisting of target parameters defined as variables. The observability of those variables determines the effectiveness of process control strategies. The developments of AI/ML have greatly enhanced the observability of various variables in metal forming using either pure data-driven (experimental data or numerical synthetic data) or hybrid data that combines both experimental and physics-based simulation data. Table 2 summarizes various target parameters used in three major forming disciplines (sheet metal forming, bulk metal forming, forming for joining) to demonstrate the intensity of the corresponding research areas. In sheet metal forming, special attention is paid to the process monitoring and control of the draw- in order to ensure a constant part quality despite deviations. Therefore, the geometry of the part or the semi-finished part is often used as the target parameter. Another approach is to consider the force curves in order to enable control of the process. Due to the high tool loads representing a special challenge in bulk metal forming, the focus of AI in bulk forming process control is on wear and maintenance prediction. As of joining processes, the aim is to control the joint design and the joint strength by minimizing the influence of disturbances. For this reason, similar to sheet metal forming, the geometry of the component or the joint is one of the central target parameters.

Despite the different focuses of target parameters in various forming operations, there exist similar end objectives in process control. A

Table 2
Target parameters of the different forming disciplines.

Forming discipline Target parameters	Sheet metal forming	Bulk metal forming	Joining by forming
Part geometry	[3,56,73,231, 250,278,281, 285,290]	[206]	[65,69,119, 147,215]
Geometry of the semi-finished part	[19,206,285]		
Draw-in	[58,68,76, 170,220,238]		
Force	[3,24,61, 232,250,273]		
Friction coefficient	[173]		
Material properties	[148,173]	[137]	
Stress	[285]	[57]	
Strain	[285]		
Process kinematics	[185,203]		[80]
Tool geometry	[19,206]		[69]
Count rate of acoustic emission	[256]		
Wear		[39,90, 266]	[230]

full feedback process control allows one to in-situ adapt process parameters for every part and therefore reduce waste and rejects. Challenges for establishing an effective and robust process control are sensing and data reduction, and control strategies that correlate data with quality criterions and process parameters. Allwood et al. [8] specifically reviewed process control for metal forming. Here in this review, the focus is given on the implementation of AI/ML in sensing and data reduction (Section 5.1) and in control strategies (Section 5.2).

5.1. AI for sensing and data reduction

Sensing is one essential element in process control. Sensing can be in-situ sensing that is used for immediate in-situ process control or can be ex-situ sensing, for example, measuring geometry of a stamped part periodically, that can affect the control decision of this particular process (e.g., deep drawing) and/or subsequent processes (e.g., redrawing, flanging, etc.). In [230], algorithms based on CNNs were used for the real-time detection of faults, caused by worn tools for instance, in a riveting process. In this case, the vibrations during riveting were detected by a sensor and on this basis, waveform-dependent images were generated that were analysed by the convolutional neural network.

Several publications focus on the acquisition of data in the running production process. For the determination of the mechanical properties, the use of eddy current as shown by Heutling et al. [107] and by Heingärtner et al. [106] is a promising approach. The magnetic properties of materials correlate with their microstructure, which also correlates with the mechanical properties. The integration of the measurement in a press shop was shown by Purr [210]. Further property measurements for the semi-finished parts are the determination of the sheet thickness by laser triangulation or of the surface condition and the amount of lubricant (Purr, [210]) on the sheet.

As presented by Fischer et al. [76] or by Doege et al. [58], the measurement of the draw-in is a suitable factor for the in-situ process monitoring of deep drawing processes. The draw-in can be measured with different physical principles. Examples for tactile measurement are shown in [58] and [238]. An approach using electromagnetic fields was proposed by Mahayotsanun et al. [170]. Embedded pressure sensors were developed for deep-drawing [222], microrolling [289], and electrically-assisted microrolling [70]. In [100], a bending process was monitored using a camera-based system to determine the bending angle. Maier et al. [171] showed the use of a camera-based measurement of the deep drawing operation after forming by measuring a skid-line. In Low et al. [165], the investigations on CNN forming prediction have proven to be a successful data-driven method that autonomously identifies features in input CAD geometries and predicts SPIF springback behavior. This predictive tool is valuable for identifying problematic areas before forming by analyzing a CAD model. Consequently, preemptive corrective measures can be taken to minimize time and resource wastage during the forming process.

Another approach in knowing the state of a forming process is through monitoring force-displacement curves. Havinga et al. [102] showed this principle for a bending operation and the correlation of the process force with the bending angle of a flange. Wiesenmayer et al. used the force-displacement curves of a cutting operation to determine the properties of semi-finished components for subsequent process steps [265].

Sensing data obtained from metal forming processes often have the characteristics of typical 5 V for data, i.e., velocity, volume, value, variety and veracity. It is highly recommended to use domain knowledge in data preparation. For example, in [119], a methodology including the use of data-based models of supervised machine learning was introduced, which enables the prediction of the expected joint properties for self-piercing riveting and additionally allows assertions about adequate joining parameters. By comparing different learning algorithms, it was shown that the size of the used data set can influence the prediction quality and that numerically determined databases with varying material properties of the sheets to be

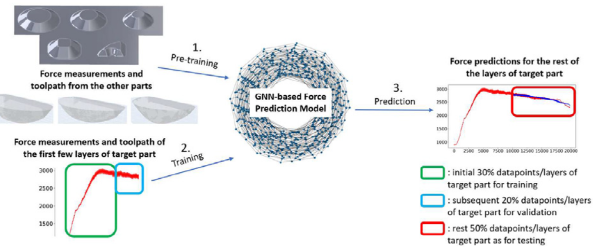

Fig. 19. GNN Model and transfer learning for force prediction in double-sided incremental forming process across different material, geometry and forming machine sizes [61].

joined, rivet properties and die geometry can be used to extend comparatively small experimental data sets [119].

Duan et al. [61] proposed a transfer learning approach using graph neural networks (GNN) to predict the entire forming force history during double-sided incremental forming processes based on the initial forming force measurement in the first few cycles. This GNN-based model was proposed to aggregate information about part geometric and toolpaths. Furthermore, a transfer learning method was adopted to improve the prediction speed, such that the model has the potential to be used in-situ process control to achieve better geometry accuracy. They experimentally demonstrated the effectiveness of the approach across several materials and machine variations (Fig. 19).

5.2. AI in control strategies

Iterative learning control (ILC) is often used for process control. ILC is an intelligent control tool, which learns from previous inputs and errors in order to improve the tracking performance of the current iteration [6]. Some applications in sheet metal forming processes are presented as follows.

Endelt and Danckert [68] proposed an ILC system for a deep drawing process comprising two nested loops. The inner loop allowed minimizing the effects of short-term process fluctuations during every punch stroke. Additionally, due to the outer loop, the system is able to react on long term process changes like varying material parameters, wear and tool temperature and thereby allows for a gradual reduction of errors resulting from long term disturbances over time. The control system is illustrated in Fig. 20. The studies were based on data gained from numerical simulations. As control variable, the flange draw-in was chosen. The compensation of fluctuations was achieved via local adjustment of the blank-holder pressure. This was realized by an elastic blank-holder design with four fluid-load cavities, which allowed for adapted pressurization and thus changing the size of the contact area. For the control system, a linear learning algorithm was used. In [67], it was shown by Endelt, that an additional fast initial response filter in the outer loop improved the performance of the iterative learning control.

Zhang et al. [281] also used an ILC model as an intelligent optimization method for a deep drawing process in order to adapt the draw bead restraining force. The model was constructed through the

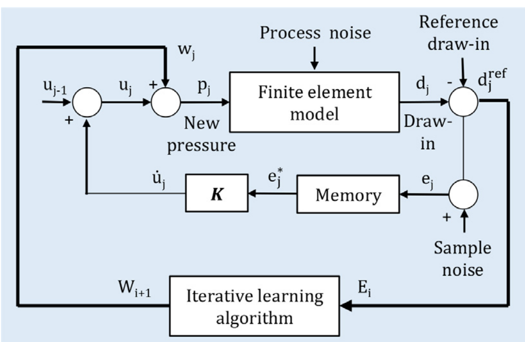

Fig. 20. Two loop control system according to [68].

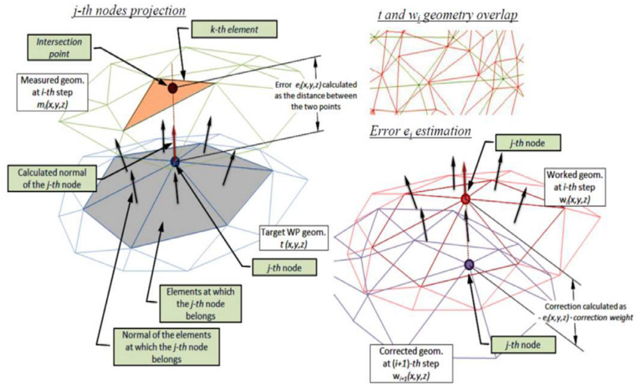

Fig. 21. Error estimation and compensation algorithm in Incremental Sheet Forming, according to [74].

imitation of the die trial process by a FE-model, which predicted the global and local forming quality near each draw bead segment for the given process parameters. The approach was verified by the numerical simulation of automotive covering panels. Using the ILC model, an adequate prediction of the draw bead restraining force without preceding experience is possible.

Fiorentino et al. [73,74] and Fisher et al. [75] used an ILC as well, but they applied this approach to an incremental forming process. In [74], the algorithm was used in a numerical simulation environment. Within the developed software, based on the desired part geometry as well as tool geometry and sheet thickness, a toolpath was created automatically. The geometry deviation between the nominal and the calculated part was examined by means of an error map. As long as the deviation exceeded a defined tolerance value, the simulation was repeated with a newly created toolpath. The error compensation algorithm considered target, measured, and corrected geometries, with meshing the geometries with j nodes. For the *i th* step, the correction (e_i) was estimated by projecting the nodes of the target t on measured geometry (m_i), and thus generating the new corrected geometry, a schematic is shown in Fig. 21. It was proven for two different geometries that within only three iterations a satisfactory accurate process result with geometry deviations less than 0.40 mm can be achieved. In [73], this algorithm was tested in experimental forming of two different part geometries. It was shown that the use of the ILC allows to compensate geometrical errors within a few steps by learning from the errors of the previous part. Similarly, in Fisher et al. [75] a method of constructing a data-driven model for use with norm-optimal Iterative Learning Controller (ILC) is developed to improve the accuracy of a SPIF process. Using in-process measurements of the sheet along with knowledge of the input, a data-driven model is constructed to optimize the input by predicting the resulting geometry from a change in tool depth. This ILC was tested on a truncated pyramid geometry, and the results showed that the controller was able to effectively reduce the process error from an MAE of 4.053 mm to 0.912 mm after five iterations.

In addition to the use of ILC, other artificial intelligence approaches are also in the focus of sheet metal forming process control. Examples include the use of artificial neural networks as well as the use of various deep learning methods, which are presented below. Yang et al. [273] were using artificial intelligence for optimization of a V-bending process of sheet metal. Force-displacement-curves of the punch in experiment were compared to curves that led to the desired bending angle in numerical variation studies. Also, springback behaviour in experiment and numerical simulation was analysed. By means of an online adaptive filter, experimental force-displacement curve and the springback value were modified in order to achieve coincidence with the output of the respective simulation. Thus, an online database was generated, which was used to control the process via an adaptation of the punch stroke. The process control system led to a very high precision of the bending angle and was expected to be transferrable to other metal forming processes.

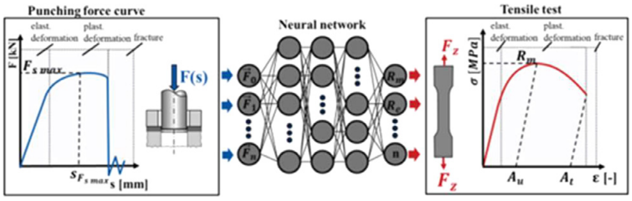

Fig. 22. Analogies between cutting force curves and stress-strain diagrams according to [232].

In [232], Schenek et al. introduced an AI-based approach to determine material parameters of different investigated dual-phase steels with the aid of an ANN. As a basis for this, the force curves during punching of the sheet materials are measured using a direct force measurement device that is integrated in the punching tool. In this way, mechanical properties of the materials can be precisely predicted and, moreover, the mechanical properties of similar materials not used for training can also be predicted. The used analogies are shown in Fig. 22**.**

The approach, as in many other cases, involves data preparation by filtering out measurement oscillations and data augmentation by multiplying the measured force curves by random arrays to achieve a high data diversity for the training of the neural networks. In further investigations [89], the same authors also used other methods besides ANN such as domain knowledge-based feature engineering, statistical feature extraction and a derivative-based method to extract features from the measurement data.

Manabe et al. [173] used a three-layered ANN for the identification of material properties in the deep-drawing process of a circular cup for improving the uniformity of thickness distribution. As input parameters for the model, punch load, punch stroke, blank-holder force, flange thickness strain and flange reduction ratio were used. The layers of the ANN were comprising 20, 40 and three neurons. For data generation, deep-drawing experiments were conducted. Based on the material parameters identified by the model, the friction coefficient during the process was determined by means of elastoplastic theory. This allowed for a prediction of the fracture and wrinkle limit for the current part using defined process curves. Based on that, an adaption of the blank-holder force was performed. The process was monitored via continuous sensing of the ANN input parameters, providing a closed loop control.

Biegel et al. [24] investigated deep learning-based monitoring approaches in order to enhance the performance of Multivariate Statistical Process Control (MSPC). Therefore, a dataset of high-frequency force and displacement sensors was used. The dataset contained curves representing normal operating conditions as well as abnormal operating conditions while deep drawing trunk lids. Using different deep learning-based methods, the monitoring of high-frequency time series data of the sheet metal forming process was possible. A comparison of the different methods showed that the best results are achieved by using a deep dense autoencoder. Similar results are obtained by using the naïve mean approach.

In Lechner et al. [148] a concept to improve the global part quality by adjusting the kinematics during a freeform bending process using a neural network is presented. Therefore, a very fast surrogate model of the process is necessary, which was trained with simulation data to compute the expected geometry. Using SVM a good accuracy was achieved. After that, the expected geometry was optimized by adjusting the process kinematics to compensate geometrical deviations due to material variations. For the real time optimization an ANN served as fast computing process model in the controller. The deviations of the bent tube ends could be reduced by an average of 52.4% using the data-based model. Recently, Zhao et al. [282] used an ANN-based feedforward feedback control to successfully improve flatness in a 1420 mm strip tandem cold rolling production line. The control scheme used within the studies is shown in Fig. 23.

To increase the geometric accuracy in a robot-based incremental sheet forming process, Störkle et al. [245] used the approach of

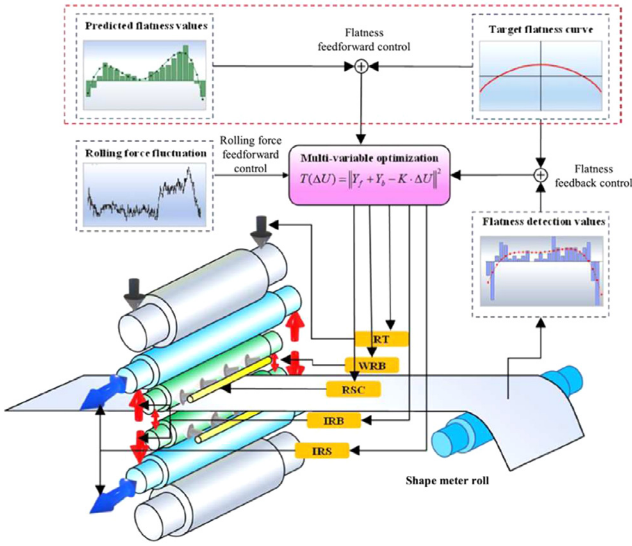

Fig. 23. Control system of the feedforward feedback coordinated regulation used in [282].

reinforcement learning. As core component served a so-called learning agent, which was able to calculate a desired geometry of the sheet metal component. With the help of this calculated geometry, the compensation of the geometric deviations was possible. Therefore, the forming tool path was adapted. The learning agent used the experiences from previous forming processes. The approach is not only limited on one geometry but can be used for several geometric shapes.

In-process geometric distortion correction also plays a major role for the work of Abdolmohammadi et al. [3], who established a virtual geometry sensing system for a robotic roll forming process. The geometry after forming is predicted on the basis of a virtual sensor for in-line robot path optimization. This approach can be exploited to enhance the process robustness by applying a geometrical correction to sheets that can be utilized for the process in this way even though they do not comply with the specified tolerances. In this context, various algorithms such as vector regression, random forest and neural networks were investigated, whereby a neural network with four hidden layers turned out to be the best-proposed model for this purpose. Furthermore, according to the investigations, there exist value ranges of parameters such as batch size, epoch numbers and learning rate, for which best values of the mean squared error are achieved. Thus, it becomes clear that hyperparameter tuning not only has an impact on the results when using neural networks but also can entail overfitting, which results in the model not being suitable for new data sets, although a high prediction quality is reached for the training data.

In an incremental forming process with an active medium an online control was used to adjust the geometry of the product autonomously. Therefore, Thiery et al. [250] integrated an axial force sensor and a laser distance sensor. The target of the control was to ensure a certain height of the formed convex truncated cone by adapting pressure with the integrated pressure chamber. The used control scheme, which is divided in a discrete control, which runs one time per forming cycle, and the continuous forming process, is shown in Fig. 24. To predict the necessary pressure an ANN was used. Besides the geometry of the formed component, the circle diameter of the tool path, the current cycle, the height difference and the average forming force were inputs for the ANN in order to predict the pressure as output. To train the network, experiments forming truncated domes of different geometries were conducted. Before the training of the ANN the inputs and the output were normalized. To validate the results, the performance of the ANN was evaluated using a training dataset. After that, the closed-loop control was validated by forming parts with different geometries while using the control system.

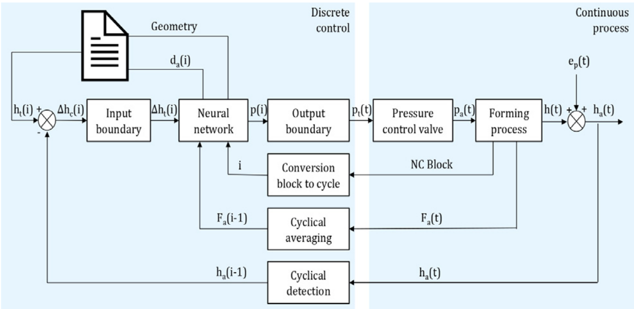

Fig. 24. Closed-loop control scheme to adjust the product height during incremental sheet forming with active medium according to [250].

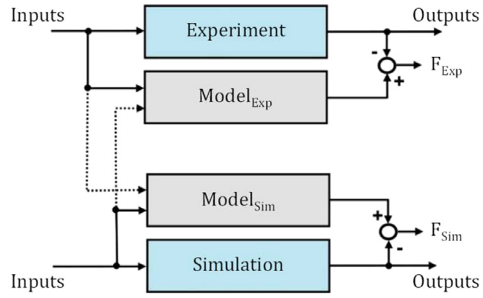

Fig. 26. Parallel paths of the real experiments (with $\text{Model}_{\text{Exp}}$) and the computer simulation ($\text{Model}_{\text{Sim}}$) according to [186].

In general, different methods are involved when using AI for process control in sheet metal forming. However, a trend towards the use of ANN is discernible. In [198], the prediction results of different machine learning methods, including Gaussian process regression, SVM, decision trees, k-nearest neighbours and ANN, are analysed and compared in the context of a SPIF process and ANN is identified as the most accurate method in this case, albeit the most inefficient in regard to training time. Park and Kang [203] used and compared a regression model and an ANN with one hidden layer for the investigation of a flexibly reconfigurable roll forming process and showed that the prediction quality of the models was dependent on the surface shape of the parts. For this reason, it is currently still the case that an appropriate method must be selected depending on the actual framework conditions and that a balance must be made between the required prediction accuracy and the training time and effort. In [2], it is shown that data obtained by a load cell during a robotic roll forming process can be used for the prediction of the workpiece geometry. The authors apply and compare linear, polynomial, and exponential regression. They achieve the best results using second degree polynomial regression. In a next step, the neural networks are used for in-line robot path optimization [3].

The artificial neural network approaches can be used to predict the forming force or volumes during flange forming. Rasche et al. [213] used the open-source machine learning library, LIBSVM, for this purpose. This resulted in an accurate prediction of more than 0.998. A disadvantage here is that this approach only considers one spot because the data cannot be separated. Furthermore, investigations by Kirchen et al. [136] showed that these approaches can also be applied to a flexible rolling process for the production of customized semi-finished products, whereby fundamental relationships between process and quality parameters could be determined using data-driven methods. Here, the predictive model is set up using incremental regression modeling and subsequently evaluated with the aid of process and quality data. Since the stroke prediction model is affected by preceding strokes, a stepwise prediction is required, as

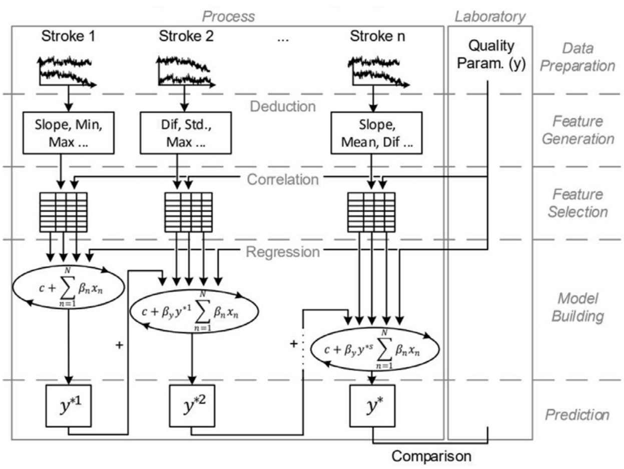

Fig. 25. Incremental regression for discrete processes [136].

shown in Fig. 25. The quality parameter describing the homogeneity of the sheet thickness of the semi-finished product could be predicted with a maximum deviation of 5%. It allows one to derive adapted parameter settings between process steps for a product, which offers the possibility to intervene during the production of a product and to optimize the control.

Nemati et al. [186] presented an approach for modelling self-piercing riveting with the aid of local fuzzy pattern models with a multidimensional membership function, which allows to predict relevant output parameters and can build the basis for process control aiming on increasing efficiency while ensuring a high product quality. This involves a coupling of the parallel paths from experiment and simulation and enables an interaction between the two models, as shown schematically in Fig. 26.

5.3. Summary of process control

In summary, the examples provided illustrate how artificial intelligence methods are used to improve forming processes and increase component quality. A major challenge for the application of AI in the field of forming technology is the acquisition and structured analysis of training data. Data preparation and the generation of larger and additional data sets to provide sufficient variety of data for training have a crucial impact on the results. However, it is not only the quantity of data that is decisive in this regard but especially the quality of the data. It is known from various studies, for example in the field of biomedical engineering [252] and materials science [255], that good results with sufficient predictive accuracy are also achievable on the basis of small data sets when using machine learning methods. Moreover, data acquisition plays a major role when using AI methods for process control in forming processes because the accuracy of the models depends on the sensors used to obtain data. This aspect is already known from research activities related to other manufacturing technologies. Groche et al. [92] demonstrated the impact of sensor types and sensor positions on the measurement results in a shear cutting process. Within the framework of the wear analysis using a multiclass support vector machine for a blanking process in [142], it was also shown that the sensors utilized and the measurement methods can lead to differences of time signals, which in turn influences the model performance. In view of these findings, it can be assumed that sensor technology also has an impact when implementing AI methods for the process analysis and control of forming processes. Therefore, attention needs to be paid to this in the future.

In cases already high-quality process knowledge is available, often individual solutions, but no transferable knowledge is provided by AI. On the one hand, the generalizability of the models must be evaluated in future studies, on the other hand the potential of other mathematical approaches, e. g., graph theory, has to be investigated. Approaches from rule-based to learning AI are used in all areas. Almost all applications involve the creation of models to link the input variables of the process with the target variable that is of interest. In terms of models, the trend is generally already towards neural networks, which is also shown in Table 3. This can be seen for all forming disciplines. The use of different algorithms depending on whether, for example, sheet or bulk metal forming is concerned, has

Table 3
AI approaches of the different forming disciplines.

	NN	GA	ILC	Class.	Reg.	Others
SMF – Refs.	[3,19,24, 81,89,173,185, 203,206,232, 250,256,285]	[231,285, 290]	[67,68,73, 281]	[56,142]	[3,185,203]	Adaptive filter [273], PCA-based [24], RL [278], Random Forrest [3]
SMF- # Data sets	25 [185] to 480 [232]	15 [231] to 48 [285]	N/A	170 [56] to 10 K [142]	12 [3] to 27 [203]	12 [3] to 273 [24]
BMF – refs.	[39,57,90,137,266]					Fuzzy [151]
BMF – Data sets	100 [39] to 315 [90]					
JF – refs.	[80,119,147,215]			[69]		Fuzzy [186]
JF - # of data	27 [147] to 312 [215]			2376 [69]		125 [186]

SMF – Sheet metal forming; BMF – bulk metal forming; JF – Joining by Forming; GA – Genetic Algorithm; ILC – Iterative Learning Control; Class. – Classification; Reg. – Regression.

not yet become evident. Nevertheless, the method must be chosen depending on the required prediction accuracy of the model, as usually an increased accuracy is also accompanied by an increased time for training. The main differences of the applied approaches relate to the processed data (e. g., machine data, image recognition or noise), for which the quantity and quality of the training data is one of the main challenges in terms of reliable functioning of the models. If a large number of datasets is used, usually numerical simulation is applied to create the respective database. However, the investigations regarding AI in forming processes are mainly on a laboratory scale. In case of experimental datasets, sensors are needed to record the input variables. In the field of sheet metal forming, the sensor-based input predominantly relates to forces and geometric quantities of the component. This trend can also be seen for bulk metal forming, whereas in joining by forming, process parameters are mainly preset and part geometry is measured after the process is finished. Sensors are used to measure acoustic emission, forces, strokes, draw-in, part height, pressure, and displacement. At the moment, it is difficult to generally differentiate between areas or use cases, what seems to be a trend for future activities.

6. AI for qualification and certification

The uncertainty associated with numerous process parameters such as tool configurations, material properties, lubrication conditions, and machine settings can lead to large variance in product quality for metal forming processes. Defective products that need to be reworked or disposed cause a significant loss in the economic value of the manufacturing process. The focus of this section is on using AI techniques for qualification of reliable manufacturing processes and certification of defect-free products.

Currently, common industrial practices heavily rely on manual inspections of various causal parameters based on expert experience. Analytical prediction of the product quality from process parameters simply fails for most cases due to the highly tangled nonlinear relationship [144]. From the input process parameters to the output part quality, there are many intermediate hidden states that are not accessible or measurable, e.g., temperature distribution in the forming zone of a double-sided incremental forming process is almost impossible to measure [126]. Simulation-based approaches have found their values in predicting these "invisible" intermediate phenomena with physical models and numerical solutions, eventually generating predictions of concerned properties of the as-built parts [270]. However, the usefulness of pure numerical simulations for product qualification and certification is questionable in metal forming processes. The accuracy of numerical predictions is affected by many factors, e.g., model inconsistency with real physics, numerical discretization errors, and lack of understanding of the fundamental mechanisms. Also, the rich sensorial and monitoring data obtained from manufacturing processes are nontrivial to be incorporated into numerical simulations; in many situations, experimental data is only

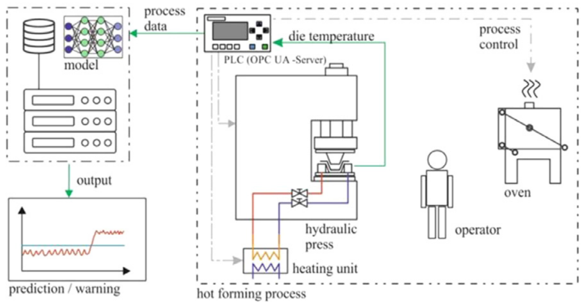

Fig. 27. Anomaly detection with machine learning models for a hot forming process [187].

used for calibrating certain parameters. In addition, the high computational cost prohibits numerical simulation from being used in real-time monitoring scenario where a slight delay in response can cause massive production of failed products.

The adoption of AI techniques for fast and reliable product quality control is of increasing interest. An example is shown in Fig. 27, where machine learning methods can be applied in real-time anomaly detection for a sheet metal hot stamping process [187]. In the following discussions, the focus is given on challenges and opportunities of using AI-based methods starting with model architecture (Section 6.1), followed by data quality (Section 6.2), and knowledge transfer and sharing (Section 6.3).

6.1. Model architecture

Innovations in designing ML models, e.g., advanced neural network architecture, help to enhance model capability and achieve higher performance when solving metal forming qualification tasks. Huang et al. [115] employed the attention mechanism and proposed deep attention residual convolutional neural network (DARCNN) to recognize surface defects for hot-rolled steel strip; compared with the sub-optimal models, the accuracy, precision and area under curve (AUC) of DARCNN are improved by 1.17%, 1.03% and 0.58%. The architecture of DARCNN is shown in Fig. 28, which contains 8 residual blocks, 1 squeeze-and-excitation block, 1 global average pooling layer, 2 convolution layers, 4 max pooling layers, and 2 dense layers. Deep neural networks can also be combined with classic ML models to generate better overall performance. For example, Boudiaf et al. [29] developed an intelligent recognition system of surface defects for hot-rolled steel strips images using modified AlexNet convolution neural network and support vector machine model. Another possibility for model improvement is to use ensemble methods that adopt multiple ML algorithms/models to obtain better performance than any of the constituent learning algorithms alone. For the prediction of defects in sheet metal forming processes, Dib et al. [55] showed that their ensemble predictive models present relatively high performances compared to the single learning model.

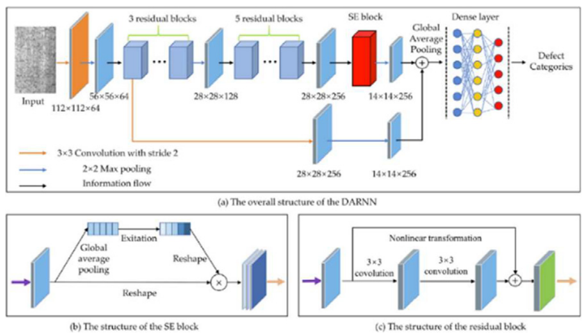

Fig. 28. The architecture of the deep attention residual convolutional neural network (DARCNN), according to [115].

Another interesting direction is the combination of physics-based models with data-driven ML models. For mass production, AI methods can be more statistically driven by abundant data; in the case of one-of-a-kind production, it becomes particularly meaningful to fuse physical models (often in the form of physical simulations) with limited experimental data. Relevant works in metal forming include [127], where a hybrid approach was proposed by combining ML techniques and physics-based kinematics model for tool wear prediction in edge trimming of carbon fibre-reinforced polymers. In our opinion, the future trends of quality control problems will involve more integrated analysis where experimental characterization, physical simulation, and AI-based methods all play indispensable roles. For example, to study the influence of composition and heat treatment on the rolling contact fatigue of hypereutectoid pearlitic steels, Solano-Alvarez et al. [242] combined experimental synchrotron measurements and neural network analysis and discovered that hardness, attained by increasing the cooling rate from the hot rolling temperature, is the most important factor. In other fields like metal additive manufacturing, a representative work can be found in [214], where high-speed synchrotron x-ray imaging and thermal imaging were coupled with multi-physics simulations, based on which ML models are trained for the prediction of keyhole porosity defect.

6.2. Data quality

Data fuels machine learning algorithms. Due to the time and cost of manufacturing processes, acquiring sufficient high-quality data to successfully train a machine learning model is often a challenge. Without enough data, the ML model is prone to overfitting in the sense that it is perfect on training data but has poor performance on test data. On the one hand, relatively cheap and abundant simulation data can supplement expensive and sparse experimental data as a strategy of data augmentation [143]. On the other hand, synthetic data augmentation can be realized by a suite of techniques to enhance the size and quality of training datasets so that better machine learning models can be built [236]. In a surface defects detection task for hot-rolled steel strip, Jain et al. [121] augmented their dataset with classic methods (e.g., random translation, rotation, and scaling of the images) and obtained a prediction accuracy of 90.28%; the same original dataset was also augmented with synthetic images generated from a GAN method and the accuracy is enhanced to 95.78%. On tool wear classification for a blanking process, Molitor et al. [180] used basic image manipulation, different types of GAN and their hybrid application to improve the accuracy of prediction up to 18% (see Fig. 29 for GAN-synthesized images). In a more recent work about surface roughness prediction, Cooper et al. [47] reduced the error of prediction from 58% to 9.1% with data augmentation by a conditional GAN.

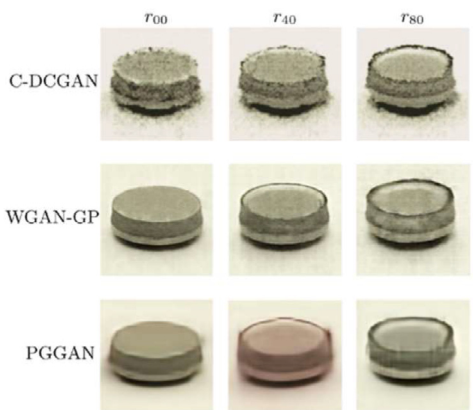

Fig. 29. Synthesized images of three different GAN models (row) for three wear classes of different cutting punch radii (column), according to [180].

Besides data insufficiency, imbalanced dataset is another challenge that critically affects the success of AI for quality control. In a typical defect detection situation, most of the data collected will be defect-free. Highly imbalanced data poses serious challenges on training the ML models as they will bias towards the majority class, and in extreme cases, may ignore the minority class altogether [129]. Common strategies on solving this problem include over sampling of the minority class, under sampling of the majority class, using the right evaluation metrics, etc. For example, Tan et al. [247] used a conditional GAN to generate synthetic minority fault class images so that the dataset is more balanced.

Similarly in a surface inspection task, Zhou et al. [284] employed a deep convolutional generative adversarial network so that synthetic image data with defect is generated and used to achieve an overall classification rate of 0.9174. Rather than direct augmentation of the minority class data, Heger et al. [104] proposed an interesting alternative solution in anomaly detection for formed sheet metals. Instead of employing a CNN for direct prediction, they used a convolution autoencoder trained only on defect-free data, and the model identifies anomalies at the deployment stage by checking if the reconstruction error is larger than a threshold. In our view, the issues associated with imbalanced dataset is underappreciated and needs more attention of the community.

Although most existing works on quality control collect and use image-based datasets, other formats of data exist and can be useful, and are usually used with models other than CNNs. In [91], signals of acoustic emissions are employed to train a ML model to classify galling wear on sheet metal stamping tools, where an accuracy of 97% is reported with regression tree (CART) technique. Chen et al. [43] extracted historical multivariate time-series data of a cold rolling process in a run-to-failure manner and trained recurrent neural networks for strip breakage prediction.

For supervised learning, raw data must be labelled, a process that is usually time-consuming and may incur high costs. Innovations can be made by automating this process for cost-saving. In a rolling surface defect inspection task, Tao et al. [249] proposed a new AI-based labelling method called Padua Incremental Mask Labelling Method to accelerate the labelling process and the data was used to train a You-Only-Look-Once-OurNet (YOLO—OurNet) deep-learning network for defect prediction.

Finally, it should be noted that not all tasks require "big data" for training. In certain applications, "small data" also lead to satisfactory results. For example, ML models are built successfully for a SPIF process with only 5–20 samples [164] and for a hot stamping process with 64 samples [283]. Gradually and adaptively increasing the size of datasets when overfitting occurs is a recommended strategy. Similarly, the number of features for each data point need not be always large. For example, in an anomaly detection task about scrap floating event in stamping, Ohashi [194,195] showed that with only six suggested features the prediction accuracy outperformed that of the traditional 'center-of-gravity' method.

6.3. Knowledge transfer and sharing

From the perspective of Bayes' Theorem and statistical machine learning, training a model is considered as finding the posterior distribution given observed data and prior knowledge. In a situation where sufficient high-quality data is sometimes difficult to obtain (like qualification data in metal forming), a strong prior can be valuable. For example, Mondal et al. [181] proposed to build a prior based on existing manufacturing knowledge sources like the Failure Mode and Effect Analysis (FMEA) and use the prior to guide the data-driven learning process of a Bayesian network. Knowledge gained from solving previous similar problems can be transferred and applied to solve the current problem. In this spirit, readers can refer to several review articles on transfer learning [199], few-shot learning [263] and meta-learning [112]. Several successful applications of these "knowledge transfer” techniques in forming processes have merged. Liang et al. [157] applied transfer learning by establishing a shared connected deep neural network and improved the electricity consumption time-series anomaly forecasting in aluminium extrusion processes. A similar work is performed by Neuhauser et al. [188] where transfer learning helps in real-time classification and detection of surface defect on extruded aluminium profiles. Kubik et al. [145] developed a domain adaptation deep learning method to handle the change of system configurations so that the neural network models do not need to be retrained, and the classification accuracy for finely graded wear states in a blanking process is 95%. Currently, many existing works are based on their in-house datasets. Yet, the publication of open datasets is beneficial for the community for knowledge sharing and transfer learning, and hence is encouraged. One such example is the surface defect database that contains six kinds of typical surface defects of the hot-rolled steel strip [243].

It is important that manufacturing knowledge of quality inspection can be properly managed and reused. A systematic way of extracting information, building knowledge-based systems, and performing reasoning/inference is through knowledge engineering. Powered by deep graph neural networks, knowledge graph (KG) has become an appealing approach for efficient and scalable knowledge representation through structural relations between entities [125]. Knowledge graph has proven to be a useful tool in understanding manufacturing processes better, and in particular, additive manufacturing [167]. For example, Ko et al. [139] proposed a Design for AM (DfAM) framework by adopting ontology with KGs as a knowledge base for storing both a priori and newfound AM knowledge (see Fig. 30); the goal was to improve the understanding of the influence of AM process parameters on part qualities.

Applying KG to metal forming processes creates opportunities of building shared and transferrable knowledge base that helps the quality control task. Beden et al. [21] proposed the Steel Cold Rolling Ontology (SCRO) to model and capture domain knowledge of cold rolling processes and built a KG for data access, data integration, data querying, and condition-based maintenance purposes. Jing et al. [128] made an attempt in information extraction and domain knowledge graph construction for hot strip rolling based-on a language model. A relevant work for sheet metal forming that used knowledge engineering but not KG can be found in [141] where the authors built a system called Knowledge Discovery in Time series and image data in Engineering Applications (KDT-EA) for wear detection.

Manufacturing processes are often distributed and require the connection and cooperation of individual manufacturing systems for efficient, on-demand production. Each manufacturing unit holds the knowledge that can be shared and transferred for training better AI models. In the previous discussion, the management and reuse of manufacturing knowledge were emphasized; here, the focus is given

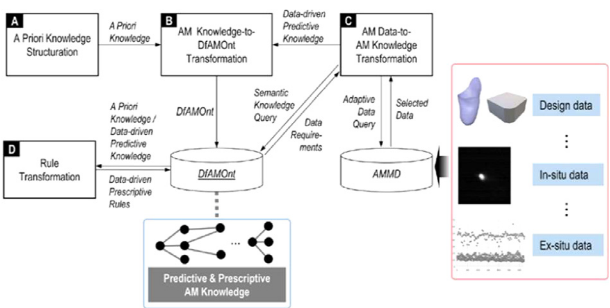

Fig. 30. Overall Data-Knowledge-Design Rule framework by adopting knowledge graphs as the storing base for part quality control, according to [139].

on federated learning algorithms that directly use distributed data without the need for centralization. Federated and distributed learning is an active research field that involves training ML models over localized data with a focus on dealing with heterogenous data, efficient communication, privacy-preserving data analysis, etc. [155]. Federated learning for manufacturing processes is applicable and promising. Truong et al. [254] proposed a lightweight federated learning-based anomaly detection for time-series data in industrial control systems. Brik et al. [32] used federated deep learning to build a prediction model of resources locations in manufacturing systems so that system disruptions are detected in real time. In a fault diagnosis task for rotating machinery, a federated learning approach was taken and its performance was examined for different data distributions across 30 participating factories [178]. Chen et al. [41] applied federated learning for better privacy protection in prediction of remaining useful life for turbofan engines. Federated learning is also applied in sheet metal forming processes to predict defects in a quality control task [49].

6.4. Summary of AI for qualification

Several aspects of effectively using AI for metal forming quality control and defect detection have been discussed. In general, the improvement of current methods can be performed either by enhancing the quantity and quality of data or through architecting novel model structures. It is also encouraged to compare and adopt useful techniques from other manufacturing processes, e.g., additive manufacturing, to better serve for metal forming.

7. Conclusions and future perspectives

A rising adoption of AI techniques in the metal forming industry has been observed, mainly for detecting defects (e.g., die wear) and predicting failures before they occur. This paper highlights a much broader range of opportunities for AI techniques, such as different machine learning algorithms and expert systems, to improve the efficiency and effectiveness of metal forming processes in the near future.

In addition to the summary section in each of Section 3 to Section 6, in which both summary and future directions were noted, here, a comprehensive overview of the benefits and future perspectives of using AI in metal forming is provided. Specifically, the provable **benefits** of using AI in metal forming include:

- (B1) AI can substitute classic constitutive models for plastic deformation, and are not restricted to special function classes such as, e.g., polynomials used to define yield criteria. They hence offer a way to unify constitutive models and make the simulation results less dependent on the choice of human operators. AI-based constitutive model are, however, much less researched than their classic physics-based and empirical counterparts, and have yet to prove that they are efficient and reliable in process simulation frameworks.
- (B2) AI algorithms such as PINN allows for predicting the outcome of entire process simulations, but have yet to prove that they can be reliably applied to large scale problems like stamping and forging.
- (B3) AI was demonstrated to improve the quality of the manufacturing process, by allowing for the real-time optimization of process variables and the identification of potential problems.
- (B4) AI techniques can significantly reduce lead time and cost by automating the optimization of process parameters. Through the use of AI approaches, it is possible to predict the performance of the forming process, and invert process models to determine the input parameters that will result in a desired output.

(B5) Tool design has been the first field of application of expert systems in the 1990s, but its seems that initial efforts in this field did not persist. New approaches such as generative design offer new ways for the design of metal forming tools but have yet to be applied to forming and proven to be effective.

Despite the rapid progress in this field, further research is needed to expand the reliability, robustness, and applicability of data-driven material modeling to today's challenging problems. Promising **future** directions include:

(F1) While physics-embedded deep learning methods have shown several ways to integrate physical principals and insights into modern deep learning networks, these methods are mainly focused on improving generalization. Vigorous studies to reveal which physical principals and methods of integration would cause stability guarantees can significantly benefit the field.
(F2) Current demonstrations of part-scale solutions are limited to relatively simple material models. While this is to some extent expected due to the sparse nature of the optimization problem, future works can push the limits of material complexity that is viable to solve using this class of methods.
(F3) Data-driven material modeling research has remained contained within simulation data, with few exceptions such as [153]. Expanding the scope of this research to include experimental training data are essential to gauge the effectiveness of these methods in various industrial applications.
(F4) Current studies do not account for the uncertainty in the measurements and process modeling. While promising early attempts have been made [114,130], further research is needed to enable the robust design of materials and manufacturing processes.
(F5) As data-driven modeling is heavily dependent on the training data and conducting experiments, or even simulations, can be expensive, investigating efficient strategies for design-of-experiment and information-rich geometries and loadings is an impactful future research direction.
(F6) Further research is needed to fully understand the relative strengths and limitations of each approach for modeling plastic deformation in different types of materials.

It is worthwhile to note that there are also several generic open research questions that need to be addressed in order to fully realize the potential of AI in metal forming. Although these points are not specific to forming, they will have a large impact on the acceptance and adoption of AI tools in forming:

(F7) Explainable AI. Explainable AI refers to AI systems that are able to provide insight into the reasons behind their decisions and predictions [13]. This is important in applications where it is necessary to understand the underlying mechanisms that drive the behavior of the system, such as in metal forming where choice of process parameters significantly impacts the efficiency of the process. At present, explainability of AI tools used in the context of metal forming is low. Thus, explainable AI is an important future research area in metal forming, as it has the potential to improve our understanding of the underlying mechanisms that govern the behavior of these manufacturing processes. This can facilitate the optimization of the process and the development of more accurate models for predicting the performance of the manufacturing process.
(F8) Extrapolation. In general, machine learning algorithms are designed to learn patterns in the training data and to make predictions based on these patterns. If the test data is significantly different from the training data, the model may not be able to generalize well and may make inaccurate predictions. This is known as the "curse of dimensionality," and can be a serious problem in high-dimensional spaces. Therefore, it is generally recommended to only use machine learning algorithms to make predictions within the range of the training data. This is difficult in metal forming, where lab scale data may not represent the entire spectrum of loading paths that the real process imposes on the material. If it is necessary to make predictions outside of the safe region, it may be necessary to gather additional data or to use a different model at present. First solutions to this problem involve the combination of machine learning and filters from control engineering such as particle filters, but more research is needed to allow for extrapolating machine learning models.
(F9) Scarcity, quality and cost of generating good training data. There are a number of strategies that can be used to use AI in fields such as metal forming, where it is expensive to generate training data and the amount of data is generally quite low. These strategies include:

- Data augmentation: One approach is to use data augmentation techniques to artificially increase the size of the training dataset. This can be done by generating additional data points by manipulating the existing data in various ways, such as rotating, scaling, or shifting the data, or by using GAN.
- Transfer learning: Another approach is to use transfer learning, which involves training a machine learning model on a large dataset, e.g., from simulations, and then fine-tuning the model on a smaller metal forming dataset [287]. This can allow the model to leverage the knowledge learned from the larger dataset, and may improve its performance on the metal forming data.
- Active learning: Another strategy is to use active learning techniques, which allow the model to actively select the most informative data points to label, rather than labeling all of the data [234]. Gaussian process models represent a sound theoretical framework for active learning. This can be an effective approach when the cost of labeling data is high, as it allows the model to focus on the most important data points.
- Hybrid approaches: Finally, it is possible to use a hybrid approach that combines multiple techniques, such as physics-based and machine learning algorithms, to leverage the strengths of each approach. This can allow for the incorporation of domain-specific knowledge and expertise into the model, which can improve its performance even with a limited amount of data.

Overall, further research is needed to understand the best ways to incorporate AI into the workflow of setting up and running forming processes, to develop methods for evaluating and explaining the performance of AI models, and to allow AI models to extrapolate beyond the space spanned by their training data. Finally, (F10) the emergence of Large Language Model (LLM) [131] such as ChatGPT (natural language processing chatbot driven by generative AI technology) or copilot tools provides a potential new way for tool design or for capturing tacit knowledge that has been accumulated in our metal forming business over decades. These LLM models need to be trained on large data, which can be extracted from past publications or patents - the outcome of rich scientific research and practices over the humankind history. However, the challenge of having consistent data interruptions and the need of critical thinking skills will require the interwoven and the co-development of both physics-based approach and data-driven approach.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Jian Cao: Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Markus Bambach:** Writing – review &

editing, Writing – original draft, Visualization, Validation, Resources, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Marion Merklein:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mojtaba Mozaffar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Tianju Xue:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation.

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Appendix

To assist readers for easy references, Table 4 summarizes the abbreviations used in this paper.

Table 4
List of Abbreviations.

AI	Artificial Intelligence	FLD	Forming Limit Diagram	MCTS	Monte Carlo Tree Search
AM	Additive Manufacturing	GAN	Generative Adversarial Networks	NN	Neural Networks
ANN	Artificial Neural Networks	GB	GB	NLP	Natural Language Processing
AUC	Area Under Curve	GD	Generative Design	PDE	Partial Differential Equation
BPNN	Back Propagating NN	GNN	Graph Neural Network	PINN	Physics-Informed Neural Networks
CART	Classification and Regression Tree	GP	Genetic Programming	RBF	Radial Basis Function
C-HiDeNN	Convolution hierarchical deep-learning NN network	GRU	Gated Recurrent Unit	RBFNN	Radial Basis Function Neural Network
CNN	Convolution Neural Network	HiDeNN	Hierarchical Deep-learning Neural Network	ReLU	Rectified Linear Unit
DAEM	Deep Autoencoder Energy Method	HiDeNN-FEM	HiDeNN-Finite Element Method	RF	Random Forest
DARCNN	Deep Attention Residual Convolutional NN Network	ICME	Integrated Computational Materials Engineering	RL	Reinforcement Learning
DDPM	Denoising Diffusion Probabilistic Models	IF	Increment Forming	RNN	Recurrent Neural Network
DEM	Deep Energy Method	ILC	Iterative Learning Control	RSS	Radial Stress Superposed
DfAM	Design for AM	KDT-EA	Knowledge Discovery in Time Series and Image Data in Engineering Applications	RVE	Representative Volume Element
DIC	Digital Image Correlation	KF	Kalman Filter	SCRO	Steel Cold Rolling Ontology
DNN	Deep Neural Network	KG	Knowledge Graph	SPD-NN	Symmetric Positive Definite Neural Networks
DS	Differentiable Simulators	LIBSVM	Open-Source Machine Learning Library	SPIF	Single Point Incremental Forming
ECNN	Equilibrium based Convolution Neural Network	LMSC	Linearized Minimal State Cell	SVM	Support Vector Machine
FCC	Face-Centered Cubic	LSTM	Long-Short Term Memory	SVR	Support Vector Regression
FCNN	Fully Connected Neural Network	ML	Machine Learning	TB	Terrabyte
FEA/ FEM	Finite Element Analysis/ Finite Element Method	MSPC	Multivariate Statistical Process Control	VUMAT	User Material Subroutine for Explicit FEM Code

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