Machine Learning in Electric Motor Production – Potentials, Challenges and Exemplary Applications

Andreas Mayr, Johannes Seefried, Marco Ziegler, Michael Masuch, Alexander Mahr,
Johannes v. Lindenfels, Moritz Meiners, Dominik Kißkalt, Maximilian Metzner, Jörg Franke
Institute for Factory Automation and Production Systems (FAPS)
Friedrich-Alexander University Erlangen-Nuremberg (FAU)
Nuremberg, Germany
Andreas.Mayr@faps.fau.de

Abstract—**Artificial intelligence entails a wide range of technologies, which provide great potential for tomorrow's electric motor production. Above all, data-driven techniques such as machine learning (ML) are increasingly moving into focus. ML provides systems the ability to automatically learn and improve from data without being explicitly programmed. However, the potential of ML has not yet been tapped by most electric motor manufacturers. Therefore, this paper aims to summarize potential applications of ML along the whole process chain. To do so, basic methods, potentials and challenges of ML are discussed first. Secondly, special characteristics of the application domain are outlined. Building on this, various ML approaches directly relating to electric motor production are presented. In addition, a selection of transferable approaches from related sectors is included, as many ML approaches can be used across industries. In conclusion, the given overview of different ML approaches helps practitioners to better assess the possibilities and limitations of ML. Moreover, it encourages the identification and exploitation of further ML use cases in electric motor production.**

Keywords— electric motor production, machine learning, artificial intelligence, potentials, challenges, applications

I. Introduction

Recent trends like natural language processing, autonomous driving, service robotics or Industry 4.0 (I4.0) are mainly based on the tremendous progress made in the field of artificial intelligence (AI) [1]. Above all, machine learning (ML) techniques are of utmost importance, allowing computers to learn from data without being explicitly programmed [3]. The increased data availability coupled with affordable computing power and extensive software solutions have laid the foundation for using such algorithms in a wide range of industrial applications, e.g. for predictive maintenance, quality management or process control [1, 2, 4].

However, since ML draws upon computer science and mathematics, manufacturing companies are facing significant challenges in making use of such advanced theories [1, 2]. In addition to a lack of data science skills, poor data availability and quality often pose a major obstacle [5]. In many cases, plants must first be equipped with additional sensors in order to acquire the right data in the right quantity before useful ML applications can be implemented [6]. In order to identify economically viable ML use cases in production, a process-oriented, less IT-driven approach is required, which incorporates existing domain knowledge about the respective manufacturing processes [6, 7].

Being confronted with increasing requirements due to electric mobility and continuing industrial automation, efficient, flexible and reliable manufacturing processes in electric motor production are more important than ever. As classical process improvement methods such as Six Sigma are increasingly reaching their limits, ML is seen as the means to meet the ever rising requirements in terms of time, costs and quality [8]. Therefore, the intelligent analysis of process and quality data promises great potential for tomorrow's electric motor production. However, electric motor manufacturers often lack suitable data to make use of the latest ML methods. While automobile manufacturers and suppliers have always demanded high traceability in manufacturing processes [9], the situation is different for manufacturers of motors for industrial applications. After all, a clear identification of each component and assembly along the process chain, e.g. by an engraved barcode, is always accompanied by additional costs. Especially for small and medium-sized companies, each electric motor is usually given a unique serial number only at the end of the line. Therefore, any process and quality data can only be assigned batchwise, not to the individual motor and its components, significantly limiting the use of ML. Accordingly, considerable investments would have to be made before ML could actually be used. This also raises the question of what ML can be actually used for and for which of the possible use cases the additional efforts ultimately pay off.

So far, only a few studies have dealt with the potentials of ML in electric motor production, indicating first useful application scenarios [10, 11]. Building on preliminary work, this paper is dedicated to give a structured overview of exemplary ML use cases along the whole process chain of electric motor production. For providing the necessary basics, section II first introduces relevant notions, methods, opportunities and limitations of ML. Furthermore, the considered application domain, the electric motor production, is characterized. Section III then shows how ML can be used in the individual process steps as well as across processes. Besides approaches directly relating to electric motor production, transferable ML use cases from related industries are included as well. Finally, the paper concludes with a summary and an outlook on further research activities.

II. Theoretical Background

As a theoretical basis, relevant terms, techniques and challenges in the field of ML are outlined in the following. The section concludes with an overview of electric motor production including the various process steps.

978-1-7281-4319-4/19/$31.00 ©2019 IEEE

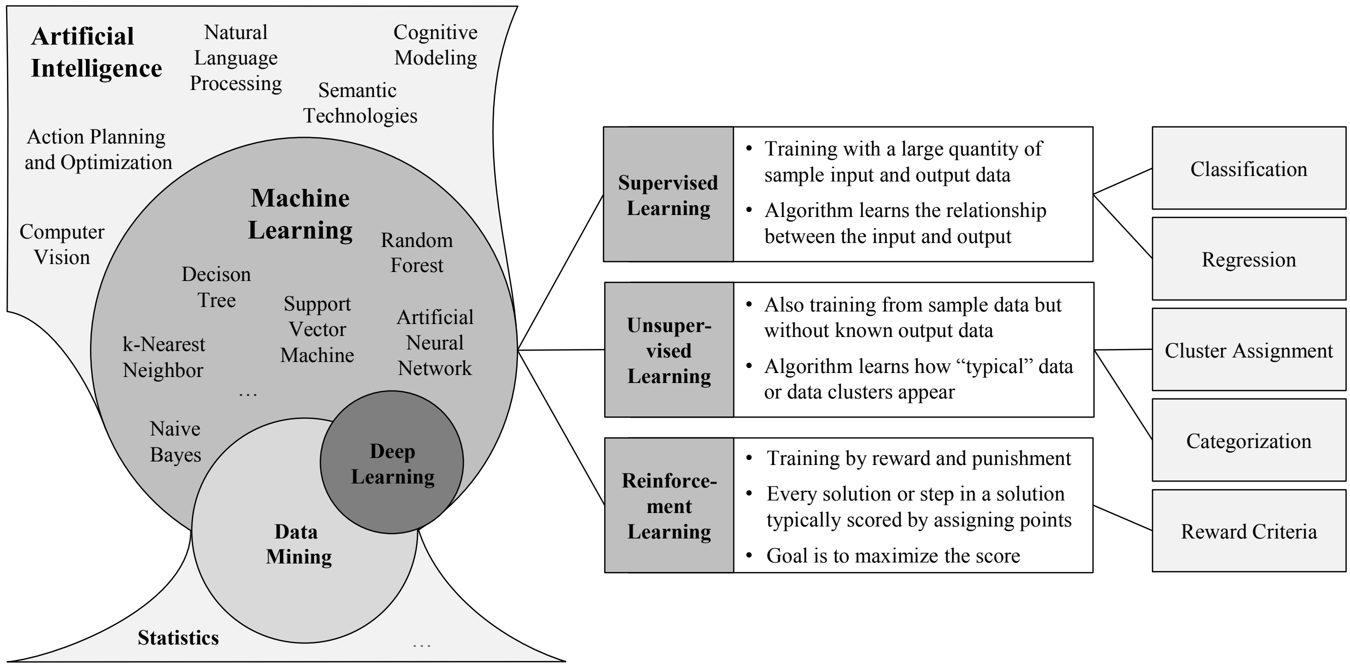

Fig. 1. Classification of the different terms and methods in the field of artificial intelligence and machine learning based on [1, 2]

A. Brief Overview of Terms and ML Techniques

According to Russel and Norvig [12], AI comprises technologies that enable technical systems to perceive their environment, to process the perceived and to solve problems independently while learning from the consequences of prior decisions and actions. ML is one of these technologies, giving computers the ability to learn without being explicitly programmed [3]. As ML-based systems aim to act as optimally and appropriately as possible, ML belongs to the rational AI approaches, together with computer vision as well as action planning and optimization [1]. In addition, there are behavior-orientated approaches such as natural language processing, semantic technologies and cognitive modeling, as stated by the authors in [1]. Like data mining, ML originates from statistics [13]. The difference is that statistics explains what happened, data mining reveals why something happened and ML determines what will happen and how a particular situation can be optimized or even avoided [2].

With ML, a basic distinction is made between supervised, unsupervised and reinforcement learning (Fig. 1). In supervised learning, the ML model is trained based on a data set consisting of pairs of inputs and outputs. Supervised learning aims to find patterns within the training data that can be used, for example, to predict the product quality based on production data. While the output value is discrete for classification, it is continuous for regression. In unsupervised learning, the computer also learns from data but without previously known output data. Instead, the algorithm learns, for example, what typical sensor data of a machine looks like to be able to detect future anomalies. [13] In reinforcement learning, the third type of ML, so-called agents are trained by reward and punishment. As every solution or step in a solution is typically scored, the goal is to maximize the cumulative score [14].

Depending on the application, a variety of algorithms can be used. Frequently used are artificial neural network (ANN), to which self-organizing maps or convolutional neural networks (CNN) belong. Further algorithms include, for example, support vector machines (SVM), decision trees, random forests, k-nearest neighbors or naive Bayes classifiers. In this context, the term deep learning refers to ML techniques which apply multiple data transformation steps to be particularly effective in extracting information from large data sets [15].

B. Basic Application Potentials of ML in Production

As far-reaching as ML is, as diverse are the possible use cases in production. In the field of maintenance, for example, ML models can estimate the condition of machines or tools and predict the optimal time for maintenance or tool changes [2, 16]. When it comes to quality management, ML can be used to monitor or even predict the quality of the product based on process data, whereby quality measures like checking random samples become unnecessary [16, 17]. Using ML in process control is expected to result in a higher adaptability to changing conditions, stabilizing output quality while simultaneously reducing reject rates [2, 11]. Particularly in the field of robotics, ML-based object recognition and motion planning have recently resulted in major advances [1]. Other exemplary fields of application include fault diagnostics, job shop scheduling or energy management [16, 17]. However, a universal, completed categorization of ML use cases in production is not yet known, not making it easier to identify and structure industry-specific use cases as in this paper.

C. Methods for Applying ML in Production

Analogous to I4.0 use cases, ML potentials can be derived from technological opportunities ("opportunity-push") or an existing need for optimization ("problem-pull") (Fig. 2) [10]. As the application of ML techniques only makes sense if the identified production problem or optimization possibility is suitable for it, the choice of the right use cases is decisive. The identification of relevant problems can be supported by methods such as value stream analyses, Ishikawa diagrams, process capability analyses or expert surveys. In contrast, technological possibilities result from current research approaches or industrial practice. In the next step, the identified use cases need to be specified and analyzed concerning their cost-benefit ratio. For ML projects, the data availability and quality strongly influences this analysis as extra sensors, data storages and processing capacities require additional investments. Based on the determined benefits and efforts, suitable use cases can be prioritized and selected, e.g. using a portfolio matrix. [10]

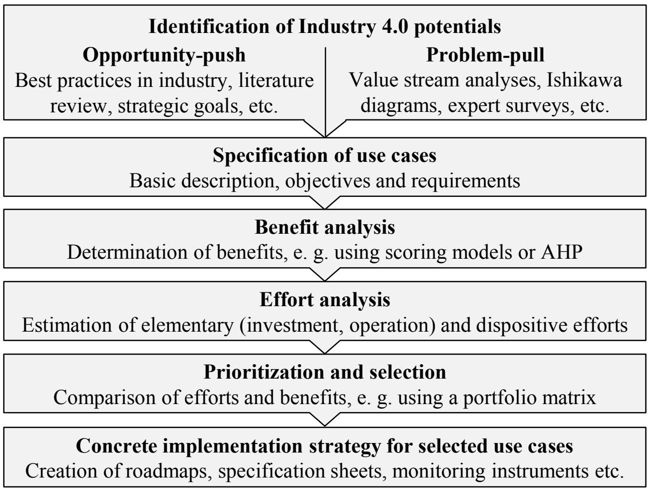

Fig. 2. Methodology for identifying and selecting I4.0 use cases [10]

For implementing ML use cases, the iterative CRISP-DM cycle with its six phases, actually originating from data mining, represents the most established method [15] (Fig. 3). The first phase, the business understanding, represents the decisive basis for a successful ML project. In this phase, the problem and the goals of the project are analyzed and defined, resulting in a project plan. The second phase, the data understanding, addresses the analysis of available data in order to gain first insights concerning the ML goals but also data quality aspects. The following data preparation phase consists of selecting, cleaning-up, constructing, transforming, integrating and formatting the available data with regard to the modeling phase and the chosen algorithms. In the subsequent modeling and evaluation phases, these algorithms are trained and evaluated with regard to defined project goals. In case of a successful evaluation, a strategy for deployment, monitoring and maintenance as well as a project report are created. [15, 18]

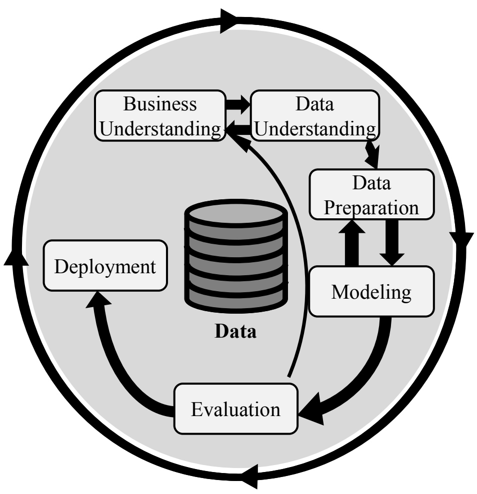

Fig. 3. CRISP-DM for implementing a ML use case [19]

D. Challenges in Using ML in Production

Like every I4.0 technology, ML is not only associated with opportunities but also with challenges. As already stated in section I, data availability and quality represent a crucial requirement for even being able to use ML [2, 5]. According to the reference architecture model RAMI 4.0 [20], this includes data from the product, field and control devices, stations, work centers, the own enterprise up to suppliers and customers. Even though the aspired implementation of the I4.0 asset administration shell in OPC UA is intended to standardize communication, machine connectivity and interoperability still represent major issues [20, 21]. Unfortunately, it is often not known in advance which data are ultimately required to train a model with an adequate accuracy [2]. This makes it all the more important to incorporate domain knowledge in order to aggregate data in a targeted manner [6].

With up to 70 %, the data preparation is usually the most time-consuming phase of a ML project [2]. As ML can only learn what it is taught, the correct assignment of valid data throughout the entire process chain has to be ensured [2]. For small amounts of data, data augmentation methods and synthetic data can be an option [22, 23]. When choosing an algorithm, not only its performance but also its robustness and explainability play a major role [1, 18]. Since the black box character of many performant ML models is usually unwanted, especially in safety-critical applications, approaches for better explainability are being researched [24].

Although the aforementioned CRISP-DM provides a rough guideline for implementing ML projects, concrete instructions and methods are still missing. Accordingly, there are approaches to combine the rather vague CRISP-DM with the well-structured techniques and tools from Six Sigma [8, 25]. Besides the project execution, the identification of relevant use cases also lacks a concrete method that includes industry-specific characteristics [7]. Thus, a structured, industry-specific use case overview as given in this paper provides a good basis for the alignment with own production problems.

E. Overview of the Application Domain

In addition to relevant ML techniques, the application domain, the production of electric motors, needs to be described briefly. Megatrends such as electric mobility or ongoing industrial automation are all built upon efficient and cost-effective electric drives. In general, an electric drive consists of an electric motor as well as all peripherals necessary for transmission, supply and control [26]. Being the second largest exporter of electric motors after China, electric motor production plays a major role in Germany [27]. Besides advancing ideas regarding the design of electric motors, the flexible automation of production processes as well as the efficient use of resources is of great importance [27–29].

In general, the main components of an electric motor are the stator and the rotor, surrounded by a housing. The production process can be divided into several sub-processes, whose exact sequence varies depending on the motor type to be produced (Fig. 4). Thus, the following explanations only represent the process chain in a very simplified way. The housing is commonly formed in a pressure die-casting process, followed by machining operations for post-processing. The laminated core, a component required for both the stator and the rotor, consists of electrical steel sheets which are usually cut out by punching. The cut sheets are then stacked and joined using techniques such as interlocking, riveting, welding or bonding. Thereupon, slot insulations and windings are mounted to the laminated core. For the latter, different winding techniques exist, such as linear, needle and flyer winding or pull-in technique. In addition, hairpin technology is increasingly being used for electric traction motors in electric vehicles. For contacting the enameled copper wires, various joining techniques can be used, e.g. crimping, welding or soldering. This is followed by the impregnation and electrical testing of the stator. Besides the stator, the rotor shaft has to be formed, machined and subsequently joined with the laminated core of the rotor. In case of a permanent magnet synchronous motor (PSM), the rotor is equipped with magnets, whereas in case of an asynchronous motor (ASM), a rotor cage is usually formed in a pressure die-casting process. In addition, other types of motors exist that are not listed here. At the end of the rotor production, possible imbalances are eliminated in the subsequent balancing process. In the final assembly, all components such as housing, stator, rotor, bearings, end shields and sensors are assembled and the motor is finally passed to the end-of-line (EOL) test. [28, 30–32]

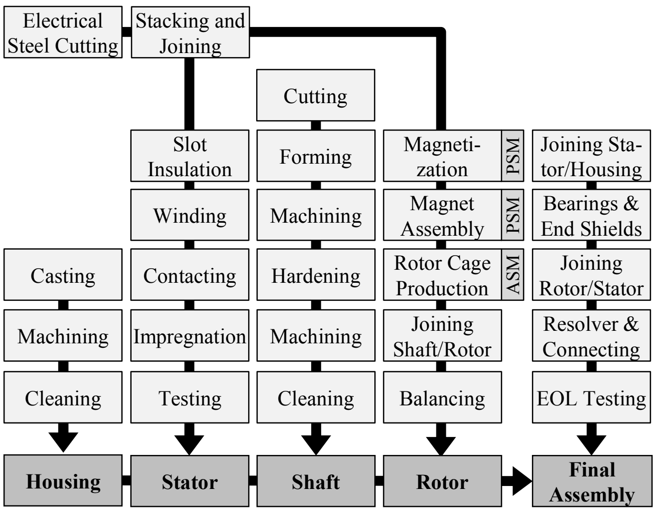

Fig. 4. Simplified production process of electric motors

III. Exemplary Applications of ML in Electric Motor Production

As already stated in section II, application potentials for ML can be either identified from a problem-pull or an opportunity-driven perspective. For the latter, literature reviews such as the present paper are suitable. On the one hand, ML approaches that directly relate to the production of electric motors are listed below. On the other hand, approaches from other industries are included that can be easily transferred to the processes addressed here.

A. *Housing and Rotor Cage Production*

For housing production, no approaches have been identified that directly address the casting of an electric motor housing. Therefore, analogies are drawn from more generic approaches. For instance, by evaluating process data and detecting implied correlations, Saleem et al. [33] apply ML for enabling an intelligent process control in foundries. In addition, Rössle and Kübler [34] present a ML approach for real-time quality prediction in die-casting based on process data acquired by high-resolution sensors. Moreover, Patel et al. [35] map the input-output relationship in squeeze casting processes using an ANN-based forward and reverse mapping, helping foundry personnel to select the right parameter set for the desired casting quality.

For the subsequent machining operations, numerous ML use cases have been found. These will be described later with the shaft production, i.e. in section III.F.

As the rotor cage of an ASM is usually manufactured by die casting, the aforementioned approaches also apply here. For small batches, the copper rods are prefabricated and then soldered to a short-circuit ring. With regard to soldering, analogies can be drawn from the contacting processes in section III.E.

B. *Laminated Core Production*

Although there are no approaches directly related to the production of electrical steel, analogies can be drawn from the hot rolling mill process of steel bars. For instance, Lieber et al. [36] use ML to identify the most striking operational patterns and to predict the resulting steel bar quality.

As is well known, the microstructure of non-grain oriented electrical steel is directly related to its electromagnetic performance. Therefore, Filho et al. [37] present a cost-effective method for the automated classification of electrical steel using ML. After training, the ML algorithm was able to reliably determine the quality class with an accuracy of over 97 %.

The electrical steel sheets can be cut out using different techniques. For punching, Slomp and Klingenberg [38] propose an autonomous process control system utilizing ANN to derive quality-indicating characteristics from the force-displacement graph. Besides, Rahman et al. [39] address the identification of defects in metal-punching processes using ANN and statistical features. Finally, Zhang et al. [40] monitor punching processes based on piezoelectric strain sensors using semi-supervised clustering.

For the laser cutting of electrical steel sheets, Pandey and Dubey [41, 42] present a hybrid approach consisting of ANN and fuzzy logic for predicting kerf width and material removal rate based on process parameters. Similarly, Lazov et al. [43] introduce an approach for predicting the surface roughness of the cut electrical steel sheets. Independent of the material, Bauer et al. [44] describe an approach for error detection on punch laser machines based on audio signals.

After being cut out, the electrical steel sheets are stacked and joined. In this context, ML approaches related to different welding processes can be considered. For laser welding, Petkovic [45] predicts the joint quality based on process parameters, while Khumaidi et al. [46] classify the resulting welding defects based on camera images using a CNN. Moreover, Günther [47] shows an intelligent architecture combining deep learning neural networks and general value functions to enable a closed loop control.

In addition, there are ML-based approaches focusing on other welding processes than laser. For instance, Chen et al. [48] use SVM for modeling gas tungsten arc welding, while Sumesh et al. [49] monitor the weld quality of shielded metal arc welding using the acoustic signature. Another use case which could be transferred to the joining of electrical steel sheets refers to the ML-based optimization of self-pierce riveting as shown by Jäckel [50].

C. Slot Insulation and Impregnation

For the slot insulation of the stator, different alternatives exist, e.g. insulating paper, powder coating or injection molded polymer insulations [28]. For the latter, analogies can be drawn from ML approaches in injection molding. For instance, Meiabadi et al. [51] combine an ANN and a genetic algorithm to determine optimal process parameters for plastic injection molding. Furthermore, Ribeiro [52] as well as Tellaeche and Arana [53] analyze in-process data for automated fault detection. In powder coating processes, ML can be used to predict the coating thicknesses as shown by Barletta et al. [54] using the example of the electrostatic fluidized bed coating.

For impregnation, various process alternatives are available, e.g. trickling, dipping or vacuum pressure impregnation. Again, only analogies can be drawn. In order to control the vacuum process effectively, Liu and Hu [55] propose an intelligent decoupling scheme using ANN, eliminating bubbles. For curing, Jahromi et al. [56] use ANNs to predict and optimize the cure cycle of thick fiber-reinforced composite parts.

D. Winding

There are also ML approaches to winding, although not many in number. In his patent, Sugimoto [57] introduces a concept for a self-optimizing coil winding machine using reinforcement learning. The proposed apparatus consists of a state observing and a learning unit. Based on the actual coil dimensions, resistance, used wire length as well as execution time, an agent is ought to adjust the machine parameters such as winding speed, tensile force or turn number. Also Kampker et al. [58] see potential in using ML for optimizing winding processes.

Independent from the electric motor production, Rodriguez et al. [59] describe a ML-based system for optimizing the wire profile generated by an automated wire winding machine. On the basis of a reinforcement learning approach, the turning point is adopted in such a way that the profile of the wire coil is as even as possible. Besides, other authors such as Wang et al. [60] deal with the ML-based optimization of tension control systems, e.g. for filament windings.

As an alternative to conventional windings, hairpin windings are becoming increasingly important [32, 61, 62]. In hairpin stator production, ML algorithms might offer potential for controlling the straightening process of hairpin wires since similar approaches can already be found for the straightening of plates, e.g. by Li et al. [63]. Analogous to the approach from Gheorghe et al. [64] in tube bending, a ML model could be used to predict the springback and dimensional accuracy in hairpin bending based on process data.

E. Contacting

With regard to contacting technologies, existing approaches that directly address the electric motor production mainly focus on crimping [11]. For thermo crimping, Fleischmann et al. [65] propose a condition monitoring system, enabling the prediction of the electrode wear as well as the contact quality. Besides, Mayr et al. [66] examine the potential of ML algorithms for ultrasonic crimping by evaluating two different use cases. On the one hand, quality-indicators such as electrical resistance and withdrawal force can be estimated based on process parameters. On the other hand, visual or acoustic features can be used to classify the joint quality. Based on this, a conceptual design for an intelligent ultrasonic crimping system is derived [67].

Besides crimping, Mayr et al. also investigate the potential of ML in laser welding of hairpin windings [68, 69]. The application of laser welding for contacting is particularly important for hairpin windings due to the high number of contact points [62]. Applying ML, it is possible to predict the quality of the weld seam based on machine parameters and images taken after the welding process. It is shown that welding defects such as pores and spatter can be detected using a CNN. Furthermore, conclusions can be drawn about the resulting electrical resistance. In future, data from previous process steps will also be included into the ML model. In particular, residues from stripping, the burr formation during cutting as well as shape deviations due to bending and twisting have a major influence on the welding result [70].

In addition, analogies can also be drawn from other joining processes, e.g. the ones described in section III.B. Independent of the electric motor production, various ML approaches to resistance welding have already been published, e.g. for predicting tensile shear strength [71], for detecting defects on weld images [72] or online quality monitoring [73]. When it comes to soldering, Liukkonen et al. [74] apply ML for analyzing, predicting and optimizing the soldering quality as well as for the final inspection of solder joints.

F. Shaft Production

After the bar material has been cut to length, a forming process usually follows. In this context, Dib et al. [75] apply ML for defect prediction in metal forming processes. In another example by Lejon et al. [76], ML is used for anomaly detection in press-hardening. Besides, Affronti et al. [77] introduce a ML approach for categorizing forming processes into multiple failure classes. For small batch sizes, however, the forming process can also be omitted so that the shape is completely produced by machining.

As shown by Kim et a. [78], different ML use cases have already been implemented in machining processes, e.g. for diagnostics and prognostics of machine tools, parameter optimization or product quality prediction. For example, Al-Zubaidi et al. [79] provide an overview of applying ANN in milling processes, focusing on the prediction of surface roughness and cutting forces as well as on the estimation of tool life and wear. Besides analyzing online process data such as vibrations and cutting forces [80], image data of the actual tool allow a direct assessment of its current state. For instance, Garcia-Ordas et al. [81] use a SVM in combination with texture descriptors to characterize each cutting edge image as worn or serviceable. Besides, Pimenov et al. [82] propose a ML approach for predicting surface roughness in real time by analyzing the main drive power. Furthermore, Kißkalt et al. [83] present a condition and process monitoring system based on pattern recognition and ML. Thereby, structure-borne sound is used to train process and behavioral models. The presented system is validated using the example of machining operations in electric drive production [84]. According to Yang et al. [85], the combination with edge and cloud computing allows for the analysis of large data streams, as generated by machine tools. The machined metal parts can then be inspected using an image fusion technique as shown by Martínez et al. [86]. Of course, the various ML approaches in machining are also applicable for the post-processing of a cast housing (see section III.A).

For the subsequent hardening of the shaft, analogies can be drawn from approaches for other heat treatment processes. For example, Oh and Ki [87] introduce a deep learning model for predicting the hardness distribution in laser heat treatment of tool steel.

G. Permanent Magnet Rotor Production

In the production of PSM rotors, various approaches exist which directly address the electric motor production. As magnetic deviations have a decisive influence on the running characteristics of the motor, there is great potential for an optimized, deviation-compensating magnet arrangement [88, 89]. In addition to conventional algorithms, ML techniques can be used for developing an optimal magnet assembly strategy. For each batch, the magnets or assembled rotor stacks are selected and mounted according to the algorithm, aiming at compensating for production-related deviations. Besides Mayr et al. [66], authors such as Coupek et al. [90–92], Colledani et al. [93] and Murakami [94] also deal with using ML for selective magnet or rotor assembly. For instance, Coupek [95] applies self-organizing maps to classify rotor segments in order to limit the solution space of the subsequent optimization, whereby saving computing time.

H. Final Assembly

In the final assembly of the motor components, different joining processes can be found: press-in operations, gluing, shrinking, screwing or welding [28]. In addition to the approaches already mentioned, analogies can be drawn from a wide range of application areas.

For the widely used screwing process, Matzka [96] introduces a ML-based approach for detecting faulty processes based on the torque curve, already patented in [97]. Also loose screws can be detected using a ML-based vision system, as proven by Ramana et al. [98]. With regard to self-tapping threaded fastenings, Althoefer et al. [99] present a strategy for the automated monitoring and failure classification using ANN. For bolt flange connections, ML can be used, for example, to predict the bold force as shown by Fei et al. [100]. With bonding, Katsiropoulos et al. [101] show how ML is used to assess the quality of adhesive bonded joints using an ANN. In addition, Tosun and Çalık [102] deal with the prediction of failure loads, whereas Domińczuk and Kuczmaszewski [103] model adhesive joints for predicting their strength.

For the final painting of the housing, analogies can also be drawn from related areas. For instance, Adams et al. [104] show how a ML-based vision system can be used to evaluate the alignment of a plasma gun nozzle using images of a test spray pattern.

I. Stator and EOL Testing

As test procedures naturally generate quite large amounts of data, ML promises great potential here. For stator testing, Guedes et al. [105] show that ML can be used to evaluate and classify failure mechanisms in electrical insulation. Further ML-based approaches for testing and monitoring of stator insulation systems can be found in a survey from Grubic et al. [106]. Besides, Halwas et al. [107] introduce a ML-based approach for analyzing the layer structure within a winding based on images taken via computer tomography.

Although most existing ML approaches refer to the monitoring of the motor during operation, analogies to the EOL test can be drawn. Accordingly, ML can be used to detect faults such as shorted coils, bearing damage, rotor imbalance or broken cages based on vibration signals [108–110], the stator current [111, 112] or both in combination [113]. For instance, Sun et al. [108] present an automated fault detection method based on vibration signals using a deep belief network auto-encoder. Alternatively, airborne sound can be analyzed as shown by Albrecht [114].

J. Cross-Process Approaches

In addition to ML use cases in individual sub-processes, there are other approaches that relate to the overall process or offer potential for different steps along the process chain.

By comparing the results of downstream product inspections with upstream production data, cross-process production influences on the product's quality can be identified. In [115], Sand et al. combine unsupervised methods, such as cluster analysis, and supervised learning, such as decision trees, to detect multivariate failure relationships efficiently. Another approach is shown by Salehi et al. [116], using a hybrid learning-based model for recognizing unnatural pattern and causes of quality problems as soon as possible. Similarly, Zhang et al. [117] present a two-step approach based on clustering and supervised learning to predict errors in production lines. Building on this, Eger et al. [118] propose an online defect prevention and defect propagation mitigation, reducing scrap and inspection efforts. Moreover, Wuest et al. [119] suggest a ML-based feature ranking method to identify and rank relevant state characteristics and thereby the processes' inter- and intrarelationships. Finally, Selmaier et al. [120] derived a method for cross-process quality analysis based on a standardized procedure mapping the CRISP-DM to RAMI 4.0. With regard to the production of electric motors, a prediction model could be developed, which links the results of the stator or EOL test to production data of the upstream process steps.

Besides, there are numerous handling steps along the process chain, which can increasingly be taken over by robots. Until now, many ML approaches address the autonomous planning and optimization of trajectories for articulated robot arms as well as sensor data processing, e.g. for 6DoF pose estimation. In this context, Blank et al. [121] present a pipeline combining CNN and template matching methods for 6DoF pose estimation in bin picking applications, especially suitable for texture-less industrial components. In doing so, the CNN helps to significantly reduce false positive pose estimates through segmentation. Moreover, Inoue et al. [122] show how a robot can successfully learn a peg-in-hole task with a tight clearance through training a recurrent neural network with reinforcement learning. In addition to reducing manual effort, the proposed method also shows a better fitting performance. Also Bobka et al. [123] increase the precision in a robotic handling task through the online estimation of assembly offsets using a deep feedforward network. In addition, Mahler et al. [124] show that unknown, randomly placed objects can be manipulated by employing CNN to learn ambidextrous grasping from synthetic training data using two or more different gripper types. In summary, these examples show that ML can greatly help to overcome major challenges in robot-based handling tasks as found in electric motor production.

TABLE I. Overview of Presented ML Approaches

Electric Motor Production		ML Approaches
Single Process Steps	Housing and Rotor Cage Production	[33], [34], [35], [78], [79], [80], [81], [82], [83], [84], [85], [86], [74]
	Laminated Core Production	[36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50]
	Slot Insulation and Impregnation	[51], [52], [53], [54], [55], [56]
	Winding	[57], [58], [59], [60], [63], [64]
	Contacting	[65], [66], [67], [68], [69], [45], [46], [47], [48], [49], [71], [72], [73], [74]
	Shaft Production	[75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87]
	Permanent Magnet Rotor Production	[66], [90], [91], [92], [93], [94], [95]
	Final Assembly	[96], [97], [98], [99], [100], [101], [102], [103], [104]
	Stator and EOL Testing	[105], [106], [107], [108], [109], [110], [111], [112], [113], [114]
Cross-Process Approaches		[115], [116], [117], [118], [119], [120], [121], [122], [123], [124]

Key: Directly or indirectly addressing electric motor production

IV. Conclusion and Outlook

As can be seen from the exemplary applications, ML holds great potential in electric motor production. Although the structured overview is anything but complete, it is already a good basis to identify own use cases from an opportunity-push perspective. However, most of the approaches mentioned are still subject of research and not yet ready for practical use or widespread. Therefore, the identification and implementation of economically viable ML use cases in electric motor production must be further promoted and, above all, the necessary data be provided.

Especially in the production of electric motors, the often low availability of data poses a major obstacle. Accordingly, the number of ML approaches directly related to electric motor production is still limited. Existing use cases mainly focus on processes such as contacting, magnet assembly and EOL testing. Also in the processing of electrical steel and the winding of coils, first approaches can be found. Furthermore, multiple promising approaches can be derived from casting and machining processes, as used to produce shafts, housings or rotor cages. The final assembly with its multitude of joining processes holds great potential as well.

The presented use cases disclose the potentials of ML from an opportunity-driven approach. Besides that, use cases can also be identified from a problem-driven perspective. Accordingly, concrete optimization potentials are to be determined on site with industrial partners in near future. For this purpose, the methodology shown in Fig. 2 must be further developed, concretized and validated with regard to ML. In parallel, further proof of concepts must emerge from research, which can then be transferred to industry.

Acknowledgment

The presented results have been obtained in context of research activities at the Institute for Factory Automation and Production Systems of the Friedrich-Alexander University Erlangen-Nuremberg. The corresponding author A. Mayr thanks the co-authors for counselling and reviewing the paper.

References

[1] iit – Institut für Innovation und Technik in der VDI/VDE Innovation + Technik GmbH, "Potential of Artificial Intelligence in Germany's Producing Sector," 2018. [Online] Available: https://www.digitale-technologien.de/DT/Redaktion/EN/Downloads/Publikation/PAiCE_AI_Study.pdf.

[2] VDMA Software and Digitalization, "Quick Guide - Machine Learning in Mechanical and Plant Engineering," 2018. [Online] Available: https://sud.vdma.org/viewer/-/v2article/render/26018603.

[3] A. L. Samuel, "Some Studies in Machine Learning Using the Game of Checkers," *IBM J. of Res. and Develop.*, vol. 3, no. 3, pp. 211–229, 1959.

[4] Allianz Industrie 4.0 Baden-Württemberg, "Einsatzfelder von Künstlicher Intelligenz im Produktionsumfeld.," Mar. 2019.

[5] H. Heimes, A. Kampker, U. Bührer, and S. Krotil, "Potenziale und Hürden von Data Analytics in der Serienfertigung," *I40M*, vol. 2019, no. 1, pp. 57–60, 2019.

[6] Wissenschaftliche Gesellschaft für Produktionstechnik e.V., *WGP-Standpunkt KI in der Produktion*. Hannover: WGP, 2019.

[7] R. Seidel, A. Mayr, F. Schäfer, D. Kisskalt, and F. Jörg, "Towards a Smart Electronics Production Using Machine Learning Techniques," in *42th Int. Spring Semin. Electron. Technol. (ISSE)*, 2019, pp. 1–6.

[8] F. Schäfer *et al.*, "Six Sigma 4.0," *ZWF*, vol. 114, no. 3, pp. 140–144, 2019.

[9] C. Brückner, Ed., *Qualitätsmanagement: Das Praxishandbuch für die Automobilindustrie,* 2nd ed. München: Hanser, 2019.

[10] A. Mayr *et al.*, "Electric Motor Production 4.0 – Application Potentials of Industry 4.0 Technologies in the Manufacturing of Electric Motors," in *8th Int. Elect. Drives Prod. Conf. (EDPC)*, 2018, pp. 1–13.

[11] A. Mayr *et al.*, "Application Scenarios of Artificial Intelligence in Electric Drives Production," *Procedia Manuf.*, vol. 24, pp. 40–47, 2018.

[12] S. J. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach,* 3rd ed. Upper Saddle River: Prentice Hall, 2010.

[13] T. Hastie, R. Tibshirani, and J. H. Friedman, *The elements of statistical learning: Data mining, inference, and prediction,* 2nd ed. New York NY: Springer, 2009.

[14] R. S. Sutton and A. G. Barto, *Reinforcement learning: An introduction*. Cambridge, Mass.: MIT Press, 20]10.

[15] I. H. Witten, E. Frank, M. A. Hall, and C. J. Pal, *Data Mining: Practical Machine Learning Tools and Techniques,* 4th ed. Cambridge: Morgan Kaufmann, 2017.

[16] A. K. Choudhary, J. A. Harding, and M. K. Tiwari, "Data mining in manufacturing: a review based on the kind of knowledge," *J. Intell. Manuf.*, vol. 20, no. 5, pp. 501–521, 2009.

[17] J. Lenz, T. Wuest, and E. Westkämper, "Holistic approach to machine tool data analytics," *J. Manuf. Syst.*, vol. 48, pp. 180–191, 2018.

[18] P. Larrañaga *et al., Industrial applications of machine learning*. Boca Raton, Florida: CRC Press, 2019.

[19] P. Chapman *et al.*, "CRISP-DM 1.0 Step-by-step data mining guide," The CRISP-DM consortium, 2000. [Online] Available: http://www.crisp-dm.org/CRISPWP-0800.pdf.

[20] Federal Ministry for Economic Affairs and Energy (BMWi), *SPECIFICATION Details of the Asset Administration Shell: Part 1 - The exchange of information between partners in the value chain of Industrie 4.0 (Version 1.0).* Available: https://www.zvei.org/en/subjects/industrie-4-0/details-of-the-asset-administration-shell.

[21] J. Fuchs *et al.*, "I4.0-compliant integration of assets utilizing the Asset Administration Shell," in *2019 24th IEEE Int. Conf. on Emerging Technol. and Factory Automation (ETFA)*, 2019, pp. 1243–1247.

[22] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *J. of Big Data*, vol. 6, no. 1, p. 1106, 2019.

[23] J. Tremblay *et al.,* "Training Deep Networks with Synthetic Data: Bridging the Reality Gap by Domain Randomization," 2018. [Online] Available: https://arxiv.org/pdf/1804.06516.

[24] N. Schaaf, M. F. Huber, and J. Maucher, "Enhancing Decision Tree based Interpretation of Deep Neural Networks through L1-Orthogonal Regularization," 2019. [Online] Available: https://arxiv.org/pdf/1904.05394.

[25] F. Schäfer, C. Zeiselmair, J. Becker, and H. Otten, "Synthesizing CRISP-DM and Quality Management: A Data Mining Approach for Production Processes," in *Int. Conf. Technol. Manage. 2018*, pp. 190–195.

[26] M. Jufer, *Electric Drive: Design Methodology*. Hoboken: Wiley, 2013.

[27] A. Mayr *et al.,* "Sustainability Aspects of Current Market Developments, Different Product Types and Innovative Manufacturing Processes of Electric Motors," *AMM*, vol. 882, pp. 64–74, 2018.

[28] A. Kampker, *Elektromobilproduktion*. Berlin, Heidelberg: Springer Vieweg, 2014.

[29] M. Weigelt, A. Mayr, R. Böhm, A. Kühl, and J. Franke, "Quo vehis, Elektromobilität?," *ZWF*, vol. 113, no. 1-2, pp. 59–63, 2018.

[30] J. Hagedorn, F. Sell-Le Blanc, and J. Fleischer, *Handbuch der Wickeltechnik für hocheffiziente Spulen und Motoren: Ein Beitrag zur Energieeffizienz*. Berlin, Heidelberg: Springer Vieweg, 2016.

[31] S. Junker, "Prozesse und Technologien für den Elektromaschinenbau," in *Handbuch Fügen, Handhaben und Montieren*, K. Feldmann, V. Schöppner, and G. Spur, Eds., München: Hanser, 2014, pp. 751–769.

[32] A. Riedel *et al.,* "Challenges of the Hairpin Technology for Production Techniques," in *21st Int. Conf. on Elect. Machines and Syst. (ICEMS)*, 2018, pp. 2471–2476.

[33] M. Saleem, D. Hartmann, S. Malik, H. Gemming, and J. Gottschling, "Intelligente Prozesssteuerung in Gießereien," *Gießerei Rundschau*, no. 62, pp. 106–121, 2015.

[34] Rössle, M., Kübler, R., "Quality Prediction on Die-Casting Sensordata," in *13th Ann. Int. Conf. on Inform. Technol. & Comp. Sci.*, 2017.

[35] M. Patel G.C, A. K. Shettigar, P. Krishna, and M. B. Parappagoudar, "Back propagation genetic and recurrent neural network applications in modelling and analysis of squeeze casting process," *Appl. Soft Computing*, vol. 59, pp. 418–437, 2017.

[36] D. Lieber, M. Stolpe, B. Konrad, J. Deuse, and K. Morik, "Quality Prediction in Interlinked Manufacturing Processes based on Supervised & Unsupervised Machine Learning," *Procedia CIRP*, vol. 7, pp. 193–198, 2013.

[37] P. P. Rebouças Filho *et al.,* "New approach to evaluate a non-grain oriented electrical steel electromagnetic performance using photomicrographic analysis via digital image processing," *J. of Materials Res. and Technol.*, 2017.

[38] J. Slomp and W. Klingenberg, "A Proposal to Use Artificial Neural Networks for Process Control of Punching/Blanking Operations," in *Flexible Automation and Intell. Manuf. (FAIM)*, 2004, pp. 556–562.

[39] N. A. Rahman, I. Masood, and M. N. A. Rahman, "Recognition of unnatural variation patterns in metal-stamping process using artificial neural network and statistical features," *IOP Conf. Series: Materials Sci. and Eng.*, vol. 160, pp. 1–7, 2016.

[40] G. Zhang, C. Li, H. Zhou, and T. Wagner, "Punching process monitoring using wavelet transform based feature extraction and semi-supervised clustering," *Procedia Manuf.*, vol. 26, pp. 1204–1212, 2018.

[41] A. K. Pandey and A. K. Dubey, "Intelligent Modeling of Laser Cutting of Thin Sheet," *IJMO*, pp. 107–112, 2011.

[42] A. K. Pandey and A. K. Dubey, "Neuro Fuzzy Modeling of Laser Beam Cutting Process," *AMM*, vol. 110-116, pp. 4109–4117, 2011.

[43] L. Lazov *et al.,* "Evaluation of laser cutting process with auxiliary gas pressure by soft computing approach," *Infrared Physics & Technol.*, vol. 91, pp. 137–141, 2018.

[44] C. Bauer, Z.-F. Siddiqui, M. Beuttler, and K. Bauer, "Big Data in manufacturing systems engineering – close up on a machine tool," *at - Automatisierungstechnik*, vol. 64, no. 7, pp. 534–539, 2016.

[45] D. Petković, "Prediction of laser welding quality by computational intelligence approaches," *Optik - Int. J. for Light and Electron. Opt.*, vol. 140, pp. 597–600, 2017.

[46] A. Khumaidi, E. M. Yuniarno, and M. H. Purnomo, "Welding Defect Classification Based on Convolution Neural Network (CNN) and Gaussian Kernel," in *Int. Seminar on Intell. Technol. and Its Appl.*, 2017, pp. 261–265.

[47] J. Günther, "Machine intelligence for adaptable closed loop and open loop production engineering systems," Dissertation, Technische Universität München, München.

[48] B. Chen, J. Zhang, J. Feng, and S. Chen, "A Study of Welding Process Modeling Based on Support Vector Machines," in *Int. Conf. on Comp. Sci. and Network Technol.*, 2011, pp. 1859–1862.

[49] A. Sumesh, K. Rameshkumar, K. Mohandas, and R. S. Babu, "Use of Machine Learning Algorithms for Weld Quality Monitoring using Acoustic Signature," *Procedia Comp. Sci.*, vol. 50, pp. 316–322, 2015.

[50] M. Jäckel, "Potentials of Industrie 4.0 and Machine Learning for Mechanical Joining," in *Joining in Car Body Eng. 2017*.

[51] M. S. Meiabadi, A. Vafaeesefat, and F. Sharifi, "Optimization of Plastic Injection Molding Process by Combination of Artificial Neural Network and Genetic Algorithm," *J. of Optimization in Ind. Eng.*, vol. 13, pp. 49–54, 2013.

[52] B. Ribeiro, "Support Vector Machines for Quality Monitoring in a Plastic Injection Molding Process," *IEEE Trans. Syst., Man, Cybern. C*, vol. 35, no. 3, pp. 401–410, 2005.

[53] A. Tellaeche, "Machine Learning algorithms for quality control in Plastic Molding Industry," in *IEEE 18th Conf. on Emerging Technol. & Factory Automation (ETFA)*, 2013, pp. 1–4.

[54] M. Barletta, A. Gisario, L. Palagi, and L. Silvestri, "Modelling the Electrostatic Fluidised Bed (EFB) coating process using Support Vector Machines (SVMs)," *Powder Technol.*, vol. 258, pp. 85–93, 2014.

[55] Y. Liu and Q. Hu, "An Intelligent Decoupling Control Scheme for Vacuum Casting Process," in *2009 WRI World Cong. on Comp. Sci. and Inform. Eng.*, 2009, pp. 42–45.

[56] P. E. Jahromi, A. Shojaei, and S. M. Reza Pishvaie, "Prediction and optimization of cure cycle of thick fiber-reinforced composite parts using dynamic artificial neural networks," *J. of Reinforced Plastics and Composites*, vol. 31, no. 18, pp. 1201–1215, 2012.

[57] Y. SUGIMOTO Yasunori, "Machine learning apparatus and coil producing apparatus," US 2017/009 1674 A1, USA.

[58] A. Kampker, K. Kreiskother, M. K. Buning, T. Moller, and S. Windau, "Exhaustive Data- and Problem-Driven use Case Identification and Implementation for Electric Drive Production," in *8th Int. Elect. Drives Prod. Conf. (EDPC)*, 2018, pp. 1–8.

[59] A. Rodriguez, P. Vrancx, A. Now´e, and E. Hostens, "Model-free learning of wire winding control," in *9th Asian Control Conf. (ASCC)*, 2013, pp. 1–6.

[60] C. Wang, Y. Wang, R. Yang, and H. Lu, "Research on Precision Tension Control System Based on Neural Network," *IEEE Trans. Ind. Electron.*, vol. 51, no. 2, pp. 381–386, 2004.

[61] T. Glaessel *et al.,* "Process Reliable Laser Welding of Hairpin Windings for Automotive Traction Drives," in *2019 Int. Conf. on Eng., Sci., and Ind. Appl. (ICESI)*, 2019, pp. 1–6.

[62] T. Gläßel, J. Seefried, and J. Franke, "Challenges in the manufacturing of hairpin windings and application opportunities of infrared lasers for the contacting process," in *7th Int. Elect. Drives Prod. Conf. (EDPC)*, 2017, pp. 64–70.

[63] S. Li, J. Song, G. Ren, and Y. Cai, "Research on Hydraulic Control System of Straightening Machine with Nine Rolls for Plates Based on BP Neural Network PID Controller," *Advanced Materials Res.*, vol. 820, pp. 117–121, 2013.

[64] A. Gheorghe, L. Lucian, G. F. Mioara, and C. V. Adrian, "Investigations on springback of bent tubes using design of experiment and artificial neural networks," *IFAC Proc. Volumes*, vol. 40, no. 18, pp. 331–336, 2007.

[65] H. Fleischmann, S. Spreng, J. Kohl, D. Kißkalt, and J. Franke, "Distributed Condition Monitoring Systems in Electric Drives Manufacturing," in *6th Int. Elect. Drives Prod. Conf. (EDPC)*, 2016, pp. 52–59.

[66] A. Mayr *et al.,* "Potentials of Machine Learning in Electric Drives Production Using the Example of Contacting Processes and Selective Magnet Assembly," in *7th Int. Elect. Drives Prod. Conf. (EDPC)*, 2017, pp. 196–203.

[67] M. Weigelt, A. Mayr, J. Seefried, P. Heisler, and J. Franke, "Conceptual design of an intelligent ultrasonic crimping process using machine learning algorithms," *Procedia Manuf.*, vol. 17, pp. 78–85, 2018.

[68] A. Mayr *et al.,* "Evaluation of Machine Learning for Quality Monitoring of Laser Welding Using the Example of the Contacting of Hairpin Windings," in *8th Int. Elect. Drives Prod. Conf. (EDPC)*, 2018, pp. 1–7.

[69] A. Mayr *et al.,* "Elektromotorenproduktion 4.0," *ZWF*, vol. 114, no. 3, pp. 145–149, 2019.

[70] A. Kampker, P. Treichel, K. D. Kreiskother, M. Krebs, and M. K. Buning, "Ex-Ante Process-FMEA for Hairpin Stator Production by Early Prototypical Production Concepts," in *8th Int. Elect. Drives Prod. Conf. (EDPC)*, 2018, pp. 1–8.
[71] M. F. A. Zaharuddin, D. Kim, and S. Rhee, "An ANFIS based approach for predicting the weld strength of resistance spot welding in artificial intelligence development," *J. Mech. Sci. Technol.*, vol. 31, no. 11, pp. 5467–5476, 2017.
[72] Z. Guo, S. Ye, Y. Wang, and C. Lin, "Resistance Welding Spot Defect Detection with Convolutional Neural Networks," in *Lecture notes in computer science, Computer Vision Systems*, M. Liu, H. Chen, and M. Vincze, Eds., Cham: Springer International Publishing, 2017, pp. 169–174.
[73] B. Xing, Y. Xiao, Q. H. Qin, and H. Cui, "Quality assessment of resistance spot welding process based on dynamic resistance signal and random forest based," *Int. J. Adv. Manuf. Technol.*, vol. 94, no. 1-4, pp. 327–339, 2018.
[74] M. Liukkonen, E. Havia, and Y. Hiltunen, "Computational intelligence in mass soldering of electronics – A survey," *Expert Syst. Appl.*, vol. 39, no. 10, pp. 9928–9937, 2012.
[75] M. Dib, B. Ribeiro, and P. Prates, "Model Prediction of Defects in Sheet Metal Forming Processes," in *Communications in Computer and Information Science, Engineering Applications of Neural Networks*, E. Pimenidis and C. Jayne, Eds., Cham: Springer International Publishing, 2018, pp. 169–180.
[76] E. Lejon, P. Kyösti, and J. Lindström, "Machine learning for detection of anomalies in press-hardening: Selection of efficient methods," *Procedia CIRP*, vol. 72, pp. 1079–1083, 2018.
[77] E. Affronti, C. Jaremenko, M. Merklein, and A. Maier, "Analysis of Forming Limits in Sheet Metal Forming with Pattern Recognition Methods. Part 1: Characterization of Onset of Necking and Expert Evaluation," (eng), *Materials*, vol. 11, no. 9, 2018.
[78] D.-H. Kim *et al.,* "Smart Machining Process Using Machine Learning: A Review and Perspective on Machining Industry," *Int. J. Precis. Eng. Manuf.-Green Tech.*, vol. 5, no. 4, pp. 555–568, 2018.
[79] S. Al-Zubaidi, J. A. Ghani, and C. H. Che Haron, "Application of ANN in Milling Process: A Review," *Model. Simul. Eng.*, vol. 2011, no. 4, pp. 1–7, 2011.
[80] P. Waydande, N. Ambhore, and S. Chinchanikar, "A review on tool wear monitoring system," *J. Mech. Eng. Automat.*, vol. 6, no. 5A, pp. 49–53, 2016.
[81] M. T. García-Ordás, E. Alegre-Gutiérrez, R. Alaiz-Rodríguez, and V. González-Castro, "Tool wear monitoring using an online, automatic and low cost system based on local texture," *Mech. Syst. Signal Process*, vol. 112, pp. 98–112, 2018.
[82] D. Y. Pimenov, A. Bustillo, and T. Mikolajczyk, "Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth," *J. Intell. Manuf.*, vol. 29, no. 5, pp. 1045–1061, 2018.
[83] D. Kißkalt, H. Fleischmann, S. Kreitlein, M. Knott, and J. Franke, "A novel approach for data-driven process and condition monitoring systems on the example of mill-turn centers," *Prod. Eng. Res. Devel.*, vol. 5, no. 1, p. 519, 2018.
[84] D. Kißkalt, A. Mayr, J. v. Lindenfels, and J. Franke, "Towards a Data-driven Process Monitoring for Machining Operations Using the Example of Electric Drive Production," in *8th Int. Elect. Drives Prod. Conf. (EDPC)*, 2018, pp. 1–6.
[85] C.-L. Yang *et al.,* "Streaming data analysis framework for cyber-physical system of metal machining processes," in *IEEE Ind. Cyber-Physical Syst. (ICPS)*, 2018, pp. 546–551.
[86] S. Satorres Martínez, C. Ortega Vázquez, J. Gámez García, and J. Gómez Ortega, "Quality inspection of machined metal parts using an image fusion technique," *Measurement*, vol. 111, pp. 374–383, 2017.
[87] S. Oh and H. Ki, "Deep learning model for predicting hardness distribution in laser heat treatment of AISI H13 tool steel," *Appl. Therm. Eng.*, vol. 153, pp. 583–595, 2019.
[88] A. Meyer *et al.,* "Concept for Magnet Intra Logistics and Assembly Supporting the Improvement of Running Characteristics of Permanent Magnet Synchronous Motors," *Procedia CIRP*, vol. 43, pp. 356–361, 2016.
[89] A. Meyer, J. von Lindenfels, A. Mayr, and J. Franke, "Manufacturing Imperfections in Electric Motor Production with Focus on Halbach Array Permanent Magnet Rotor Assembly," in *8th Int. Elect. Drives Prod. Conf. (EDPC)*, 2018, pp. 1–7.
[90] D. Coupek, A. Lechler, and A. Verl, "Cloud-Based Control Strategy: Downstream Defect Reduction in the Production of Electric Motors," *IEEE Trans. on Ind. Appl.*, vol. 53, no. 6, pp. 5348–5353, 2017.
[91] D. Coupek, A. Lechler, and A. Verl, "Cloud-based control for downstream defect reduction in the production of electric motors," in *Int. Conf. on Electr. Syst. for Aircraft, Railway, Ship Propulsion and Road Vehicles (ESARSITEC)*, 2016, pp. 1–6.
[92] D. Coupek, A. Gülec, A. Lechler, and A. Verl, "Selective rotor Assembly Using Fuzzy Logic in the Production of Electric Drives," *Procedia CIRP*, vol. 33, pp. 550–555, 2015.
[93] M. Colledani, D. Coupek, A. Verl, J. Aichele, and A. Yemane, "A cyber-physical system for quality-oriented assembly of automotive electric motors," *CIRP J. of Manuf. Sci. and Technol.*, vol. 20, pp. 12–22, 2018.
[94] Y. Murakami, "Machine learning apparatus and method for learning arrangement position of magnet in rotor and rotor design apparatus including machine learning apparatus," US20170093256 A1.
[95] D. Coupek, *Kompensation von Magnetisierungsabweichungen in Permanentmagnet-Synchronmotoren durch selektive Rotormontage*. Stuttgart: Fraunhofer Verlag, 2019.
[96] S. Matzka, "Frühzeitige Erkennung von Fehlschraubungen mittels künstlicher Intelligenz," in *Beuth Innovation, Industrie 4.0: Safety und Security*, C. Pinnow and S. Schäfer, Eds., 1st ed., Berlin: Beuth, 2016.
[97] S. Matzka, A. Schemmerer, A. Blum, and P. Rahman, "METHOD FOR CONTROLLING A SCREWING PROCESS," US2017014961 (A1), US US201615211660 20160715, Jan 19, 2017.
[98] L. Ramana, W. Choi, and Y.-J. Cha, "Fully automated vision-based loosened bolt detection using the Viola–Jones algorithm," *Structural Health Monitoring*, vol. 18, no. 2, pp. 422–434, 2019.
[99] K. Althoefer, B. Lara, Y. H. Zweiri, and L. D. Seneviratne, "Automated failure classification for assembly with self-tapping threaded fastenings using artificial neural networks," *Proc. Inst. Mech. Eng., Part C*, vol. 222, no. 6, pp. 1081–1095, 2008.
[100] Y. Fei, G. Pengdong, and L. Yongquan, "Bolt force prediction using simplified finite element model and back propagation neural networks," in *Infom. Technol. Netw. Electron. Automat. Control Conf.*, Chongqing, China, 2016, pp. 520–523.
[101] C. Vasilios Katsiropoulos, E. D. Drainas, and S. G. Pantelakis, "Assessing the quality of adhesive bonded joints using an innovative neural network approach," *Int. J. Struct. Integr.*, vol. 5, no. 3, pp. 187–201, 2014.
[102] E. Tosun and A. Çalık, "Failure load prediction of single lap adhesive joints using artificial neural networks," *Alexandria Eng. J.*, vol. 55, no. 2, pp. 1341–1346, 2016.
[103] J. Domińczuk and J. Kuczmaszewski, "Modelling of adhesive joints and predicting their strength with the use of neural networks," *Computational Materials Sci.*, vol. 43, no. 1, pp. 165–170, 2008.
[104] S. Adams, G. Crannell, A. Bolcavage, R. McIntyre, and P. A. Beling, "A Condition Monitoring System for Low Vacuum Plasma Spray using Computer Vision," in *Int. Conf. Prognostics Health Manage. 2018*, pp. 1–7.
[105] A. S. Guedes, S. M. Silva, B. d. J. Cardoso Filho, and C. A. Conceição, "Evaluation of electrical insulation in three-phase induction motors and classification of failures using neural networks," *Elect. Power Syst. Res.*, vol. 140, pp. 263–273, 2016.
[106] S. Grubic, J. M. Aller, B. Lu, and T. G. Habetler, "A Survey on Testing and Monitoring Methods for Stator Insulation Systems of Low-Voltage Induction Machines Focusing on Turn Insulation Problems," *IEEE Trans. Ind. Electron.*, vol. 55, no. 12, pp. 4127–4136, 2008.
[107] M. Halwas, d. Binder, and J. Fleischer, *Systematische Analyse des Lagenaufbaus von Wicklungen in Nuten elektrischer Maschinen mittels räumlicher Bildgebung und maschinellen Lernens.* [Online] Available: https://www.umformtechnik.net/binary_data/3360176_analyselagenaufbau-draht-halwas.pdf. Accessed on: Mar. 30 2019.
[108] J. Sun, R. Wyss, A. Steinecker, and P. Glocker, "Automated fault detection using deep belief networks for the quality inspection of electromotors," *tm - Technisches Messen*, vol. 81, no. 5, pp. 255–263, 2014.
[109] E. Principi, D. Rossetti, S. Squartini, and F. Piazza, "Unsupervised electric motor fault detection by using deep autoencoders," *IEEE/CAA J. Autom. Sinica*, vol. 6, no. 2, pp. 441–451, 2019.
[110] Y. Huang, C.-H. Chen, and C.-J. Huang, "Motor Fault Detection and Feature Extraction Using RNN-Based Variational Autoencoder," *IEEE Access*, vol. 7, pp. 139086–139096, 2019.
[111] I.-H. Kao, W.-J. Wang, Y.-H. Lai, and J.-W. Perng, "Analysis of Permanent Magnet Synchronous Motor Fault Diagnosis Based on Learning," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 2, pp. 310–324, 2019.

[112] R. H. Cunha Palácios, I. N. da Silva, A. Goedtel, and W. F. Godoy, "A comprehensive evaluation of intelligent classifiers for fault identification in three-phase induction motors," *Elect. Power Syst. Res.*, vol. 127, pp. 249–258, 2015.

[113] M. Z. Ali, M. N. S. K. Shabbir, X. Liang, Y. Zhang, and T. Hu, "Machine Learning-Based Fault Diagnosis for Single- and Multi-Faults in Induction Motors Using Measured Stator Currents and Vibration Signals," *IEEE Trans. on Ind. Appl.*, vol. 55, no. 3, pp. 2378–2391, 2019.

[114] H.-R. Albrecht, *Akustische Fehlererkennung bei Elektromotoren: Neuronale Netze koennen das menschliche Gehoer ersetzen.* [Online] Available: https://www.computerwoche.de/a/neuronale-netze-koennen-das-menschliche-gehoer-ersetzen,1126594. Accessed on: Jan. 14 2018.

[115] C. Sand, S. Kunz, H. Hubbert, and J. Franke, "Towards an inline quick reaction system for actuator manufacturing using data mining," in *6th Int. Elect. Drives Prod. Conf. (EDPC)*, 2016, pp. 74–79.

[116] M. Salehi, A. Bahreininejad, and I. Nakhai, "On-line analysis of out-of-control signals in multivariate manufacturing processes using a hybrid learning-based model," *Neurocomputing*, vol. 74, no. 12-13, pp. 2083–2095, 2011.

[117] D. Zhang, B. Xu, and J. Wood, "Predict failures in production lines: A two-stage approach with clustering and supervised learning," in *IEEE Int. Conf. on Big Data*, 2016, pp. 2070–2074.

[118] F. Eger *et al.,* "Zero Defect Manufacturing Strategies for Reduction of Scrap and Inspection Effort in Multi-stage Production Systems," *Procedia CIRP*, vol. 67, pp. 368–373, 2018.

[119] T. Wuest, C. Irgens, and K.-D. Thoben, "Changing States of Multi-stage Process Chains," *J. Eng.*, vol. 2016, no. 3, pp. 1–11, 2016.

[120] A. Selmaier, R. Phillipe, A. Mayr, J. Fürst, and J. Franke, "Cross-Process Quality Analysis of X-ray Tubes for Medical Applications Using Machine Learning Techniques," in *Production at the Cutting Edge: Proc. of the 9th Cong. of the German Academic Association for Prod. Technol. (WGP)*, J. P. Wulfsberg, J. P. Hintze, and B.-A. Behrens, Eds., Heidelberg: Springer, 2019.

[121] A. Blank *et al.,* "6DoF Pose-Estimation Pipeline for Texture-less Industrial Components in Bin Picking Applications," in *Eur. Conf. Mobile Robots (ECMR)*, 2019.

[122] T. Inoue, G. de Magistris, A. Munawar, T. Yokoya, and R. Tachibana, "Deep reinforcement learning for high precision assembly tasks," in *IROS Vancouver 2017: IEEE/RSJ Int. Conf. on Intell. Robots and Syst.*, 2017, pp. 819–825.

[123] P. Bobka *et al.,* "Development of an automated assembly process supported with an artificial neural network," *J. Mach. Eng.*, vol. 18, no. 3, pp. 28–41, 2018.

[124] J. Mahler *et al.,* "Learning ambidextrous robot grasping policies," *Sci. Robot.*, vol. 4, no. 26, eaau4984, 2019.