A review of machine learning for the optimization of production processes

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Abstract

Due to the advances in the digitalization process of the manufacturing industry and the resulting available data, there is tremendous progress and large interest in integrating machine learning and optimization methods on the shop floor in order to improve production processes. Additionally, a shortage of resources leads to increasing acceptance of new approaches, such as machine learning to save energy, time, and resources, and avoid waste. After describing possible occurring data types in the manufacturing world, this study covers the majority of relevant literature from 2008 to 2018 dealing with machine learning and optimization approaches for product quality or process improvement in the manufacturing industry. The review shows that there is hardly any correlation between the used data, the amount of data, the machine learning algorithms, the used optimizers, and the respective problem from the production. The detailed correlations between these criteria and the recent progress made in this area as well as the issues that are still unsolved are discussed in this paper.

Keywords Machine learning · Optimization · Manufacturing · Production

1 Introduction

Together with the rising popularity of machine learning research and the growth of the available data amounts, the applications of the developed methods have found their way into various industrial fields. In this context especially, the exploitation of data for optimization in existing production lines is of high relevance [35, 53]. Optimization can take place in two different ways: on the one hand, there is the improvement of the product quality itself; on the other hand, the production process can be changed for the better.

The utilization of machine learning is motivated by its additional capabilities to spare resources, machining time, and energy and increase yield where traditional methods

such as six sigma strategies have reached their limits [53]. In the author's eyes, the term "machine learning" describes algorithms to identify and extract valuable patterns in the data: from data transformation methods (e.g., PCA), over data exploration methods (e.g., k-means clustering), and traditional methods of supervised learning for regression and/or classification (e.g., decision trees) to more recent methods (e.g., Convolutional Neural Networks). These cover a broad range of complexities, origins, and recency of the algorithms themselves, all having in common the extraction and use of specific features of the data useful to improving quality.

Though an important prerequisite for the application of machine learning for production processes, industry 4.0, industrial analytics and high-performance computing will not be discussed in detail in this manuscript. The initiation of smart manufacturing systems in existing plants can be realized by storing and processing of arising data by existing and additionally installed sensors. Due to the continuous development of new sensors, processing software, and storages on low-price level as well as the small degree of necessary interventions into a running process, the hurdles for smart manufacturing are set low.

The aim of this study is to review machine learning applications to optimize products and production processes in existing production environments from 2008

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to 2018. Since earlier years, the authors refer to the extensive review of Köksal et al. focusing on data mining applications for quality improvement in manufacturing industry [53]. Additionally, there exist more general reviews on machine learning in manufacturing that either do not explicitly concentrate on optimization issues [10, 37, 67, 92, 118] or focus on special methods and/or applications [15, 112].

The interest in the integration of machine learning and optimization algorithms in production processes has increased steadily since 2009 and has been at a consistently high level since 2014. Thus, it remains a hot topic in latest research, starting with the development of scientific methods for sensor placement, going through data storage and processing architectures, and ending with machine learning and optimization algorithms [118].

Since the field of machine learning and optimization in production processes is very wide, the authors have identified three closely related topics that will not be covered extensively in this review. The first one is optimization with methods from the field of design of experiments (DOE) and response surface methodology (RSM). Even if a DOE or RSM is used in applications, the review will not focus on the specific designs. Here, the authors like to refer the interested reader to the comprehensive work of Montgomery [68], as a detailed description of methods and applications is beyond the scope of this review. The second topic is statistical process control (SPC), pioneered by Shewhardt in 1925, which uses classical statistical analysis of the collected data for process variation reduction [93]. As the majority of publications does not fall back to the methods of "modern" machine learning, this field of research is excluded. A third topic to exclude is model predictive control (MPC) as a special field of control engineering. Here, the authors would like to refer the interested reader for example to the work of Mayne [64] and Scattolini [87]. In general, the application of machine learning methods for the optimization of production processes can take place with or without an immediate quality feedback, depending on its' availability. With a quality feedback, it is quite similar to closed loop control engineering, as it is used to adapt process parameters to improve the measured quality. But as neither the quality feedback, the process parameters and the process description itself are in the typical format used for closed loop control (feedback and parameters as time series data and the process description as a state equation), nor is there a frequent change of the parameters during a running production step, the authors will exclude this special field of research from the review.

The paper is organized as follows: firstly, the occurring data types in manufacturing are reviewed. Secondly, an overview on applications of machine learning for quality improvement without change of manufacturing parameters during the process is given. Subsequently, applications where explicit changes of manufacturing parameters are allowed are reviewed in detail. After a detailed analysis connecting data, machine learning, and optimization, a conclusion is drawn and open research questions are discussed.

2 Data in machine learning in production

The first step to solving a machine learning problem is to identify the data that is available. There are different types of data which will affect the type of analyses that can be used on them. Based on their types, the amount of information which data gives can vary considerably [11]. Data can be structured in the following ways. Topics such as data quality, missing data, or details about data preprocessing will not be addressed in this work, but may be found, for example, in [35].

2.1 Qualitative vs. quantitative data

Qualitative data can be divided into nominal data and ordinal data. Nominal data only gives the name of a category to which something belongs like the name of a material for the press hardening of a component [74]. Ordinal data indicate the order of something. For example, Neugebauer et al. [69] divide the quality of gears, which are produced by forming, into classes depending on the pitch accuracy. Quantitative data can be interval data where there is no absolute zero point such as the tool temperature in a press hardening process; and ratio data which can be used to give information about relative size, such as sheet thickness of a press hardened part at a certain point [11, 74].

2.2 Time series vs. workpiece-related data

Most commonly, a time series is a sequence or continuous signal with equally spaced points in time like the energy consumption of a machine tool over time (see for example [109]). Another possibility is data that is related to a workpiece such as the workpiece temperature during the heating of the press hardening process [74]. Such workpiece-related data can, however, also be time series data.

2.3 Controllable vs. uncontrollable data

As described in Oh et al. [72], data can also be divided with regard to their controllability. Controllable parameters can be adjusted either manually or automatically, while uncontrollable parameters may not be changed. An uncontrollable

parameter is for example the sheet thickness at the beginning of a press hardening process because this parameter is defined by the coil producer. A controllable parameter can be the time a part remains in the press.

2.4 Present vs. historical data

Another way of subdividing data may be with respect to its measurement date. Machine learning algorithms can learn from historical data and then use present data to predict future outcomes. However, it has to be taken into account that the data acquisition can be changed and adapted over time. Therefore, it may be necessary to clean up historical data, as for example described in [38] or models based on older data have to be retrained.

2.5 Measured vs. simulated data

The origin of data also plays a significant role. It is important to verify simulated data with real data. The use of both simulated and experimental data is also possible (see for example [25] where new simulations are automatically performed in order to improve the prediction quality of a platform that incorporates experimental data, computational simulations, and a machine learning model). In the case of production processes, it should also be considered that established and robust processes almost exclusively produce good parts and very few data are available for rejected parts. However, machine learning models need balanced data, so simulation plays a key role here [7].

2.6 Observable quantities vs. process state variables

In many manufacturing processes, it is not possible to measure on-line the state variable values that describe the system state and are essential for process control. Instead, only quantities related to the state variables can be observed [89]. Senn et al. [89, 90] for example describe a deep drawing process where observable quantities are forces, displacements, and strains while state variables are the high-dimensional stresses in the workpiece at various locations.

The knowledge of the structure of production data is crucial for the right choice of machine learning models. Most data coming from production systems equipped with sensors can be considered as structured data which is much easier to handle than unstructured data [85]. Another important aspect which is not the focus of this manuscript is the fusion of data from multiple sensors. More information on this topic can be found in [60] or [81]. The next section describes different approaches for a machine learning–based optimization in production.

3 Application of machine learning for optimization of production

Process optimization by machine learning can be structured into two main topics, distinguished by the adjustment of production parameters. The first is optimization without change of production parameters during the manufacturing process. Examples are root cause analyses to prevent from recurrent quality issues, early prediction of manufacturing outcomes to spare unnecessary process steps, and diagnostic methods to detect erroneous behavior of products or processing units. All examples have in common that there is no direct adjustment of the production parameters but product quality is improved indirectly.

A second topic is optimization with change of production parameters. Here, optimal production parameters are determined using the data of an already running production process. By adjusting the parameters to the characteristics of the product and the specific optimization goal, a higher quality is achieved. Implementations can be distinguished in machine learning approaches with additional optimization modules and self-optimizing control systems based on analytical process models. In this paper, only machine learning approaches are discussed.

In both (direct and indirect) approaches, the objective for optimization can be a product- or process-specific quantity. Product-specific quantities are for example surface roughness, shrinkage, and processor speed, while the energy consumption of a plant or tool wear is a process-specific one. Optimization of both types of objectives results in improved product quality defined in terms of cost, time, consumption of resources, and/or the specific optimization objective.

3.1 Optimization without parameter changes

Typical industrial applications for quality improvement based on machine learning are found in large-scale production such as plastic injection molding (PIM) and the production of semiconductors. The authors assume that this is grounded on the high amounts of usable data points provided due to short cycle times. Especially that in the manufacturing of micro-electronic parts exists long-lasting tradition (see, e.g., [4, 41] for examples for classification algorithms in industry as early as in 1993). Up to now, scientists are still challenged by imbalanced datasets, missing data, and concept drift [16, 115]. The following section provides an overview of three different approaches for optimization without change of the production parameters: Root cause analysis, early prediction of manufacturing outcomes, and diagnostic systems.

3.1.1 Root cause analysis

An obvious approach for quality improvement is the analysis of existing data records to extract relevant features and feature combinations for high or low product quality. This might be done by feature selection at a preliminary stage of learning a model or as specific root cause analysis. There exists a lot of literature in these fields (see the already mentioned reviews [10, 15, 37, 67, 92, 112, 118]) and analysts seem to be satisfied with the identification of previously unknown patterns and important features relevant to product quality. Reports on the consequences of changes of production parameters drawn from the patterns are rare.

In the sector of semiconductor manufacturing, the research of Chien et al. on root cause analysis is quite fundamental. In his work, he proposed k-means clustering [24]; principal component analysis (PCA), clustering, and decision trees [22]; stepwise batch regression algorithms with random forests [21] and feature selection together with logistic regression [23] to find root causes for poor quality and finally enhance yield.

Other authors such as Kumar et al. [56] or Diao et al. [30] apply hierarchical generalized linear models (GLM) or improved PCA and modified support vector machines (SVM) to identify dominant factors for quality and quality prediction. It is also possible to apply Gibbs Sampling for variable selection, learn multivariate adaptive regression splines (MARS) to predict semiconductor yield, and use decision tables to extract root causes [49].

Another method to find root causes for quality issues is the extraction of defect patterns. For instance, Franciosa et al. [32] analyze a multi-stage assembly system and utilize a combination of multi-physics simulations from first principles, measurement data and artificial neural networks (ANN) to identify defect patterns. In the field of semiconductor production, Wang [110] proposes the clustering of defect patterns.

Association rule mining is a method to extract interpretable relationships relevant for product quality (see [114] in semiconductor manufacturing). In drill production, Kamsu-Foguem et al. thoroughly describe the use of association rules [44].

3.1.2 Early prediction of manufacturing outcomes

In optimization of manufacturing processes, not only is product quality a highly relevant criterion, but so are the costs of production steps. If production steps are expensive in terms of time or price, it is useful to predict manufacturing outcomes beforehand. With this method, unnecessary and costly production steps can be avoided by dropping products from the production line before the critical steps. Alternatively, additive corrective manufacturing actions can be initiated, for example the correction of wafers with expected poor performance in semiconductor production [116].

The early prediction of production outcomes differs from traditional process identification in the size of the parameter set. For process identification, a full set of relevant production parameters of all processing stages is needed, while the *early* prediction already works with process parameters of an *early* relevant part of the production line, allowing to introduce correcting actions before finishing the whole production process.

But simple process identification with the full parameter set enables the so-called virtual metrology as exemplarily described by Kang et al. [45] and Khan et al. [50]. Here, the quality of the out-of-sample products is predicted by a machine learning method, saving time and costs. As this does not optimize the production process but only means a regression/classification of the production output, the authors would like to refer the reader to the work mentioned above.

The challenge of the early prediction of manufacturing outcomes is to make a reliable prediction of the final quality at early stages of the process and to identify relations between process steps. Several authors proposed solutions, e. g., the work of Lieber et al. [59] and Konrad et al. [54] for rolling mill processes with self-organizing maps (SOM) and k-Nearest-Neighbor (kNN) approaches or Arif et al. [5] for decision trees in semiconductor manufacturing. Both works have in common that no application was reported.

More promising is the work of Weiss et al. [115, 116], who estimated the final microprocessor speed after each manufacturing operation applying linear regression and boosted trees: the predictions initiating corrective manufacturing actions if necessary. The authors were challenged by the already mentioned concept drift, missing data, and imbalanced datasets. Special methods to overcome these problems were developed by Chen and Boning [16], who apply boosting and bagging of customized decision trees to predict semiconductor yield before packaging.

3.1.3 Diagnostic systems

Another way of optimizing the final quality of a product is the use of diagnostic systems within the production line. It is possible to monitor the product itself (part diagnosis) and/or the processing machines (plant diagnosis). Both approaches lead to an alarm being raised if the condition of the part or machine is anomalous or becoming anomalous, requesting correction actions to be taken.

3.1.4 Part diagnosis

For the diagnosis of parts, two main applications are described, namely visual inspection and the diagnosis of part assemblies.

Automatic visual inspection, applied before, during, and after production processes, serves to maintain good part quality, examining images for possible faults. Various methods were developed for the production of semiconductors and screen glasses [40, 43, 105], ceramics and tiles [47], and miscellaneous processes relating to metal parts [42, 63, 88, 113, 121]. Additionally, generic methods for different materials and purposes were developed [73, 80].

Methods for visual inspection vary over projection methods like independent component analysis [105] and PCA [17]; filter-based approaches like discrete cosine transform [76] and discrete wavelet transform [121]; learning-based approaches like SVM [106], Hidden Markov Models (HMM) [42], fuzzy clustering [43], and convolutional neural networks (CNN) [63, 73, 80, 113] for regression or classification; and statistical methods [88].

Diagnosis of assembly processes or its results usually uses data sources different from images, resulting in the use of different methods. Additionally, recent authors try to cover not only one specific processing stage but multi-stage processes as well. This complicates the problem to be solved due to correlations between the different process steps and the resulting error propagation. For sheet metal assemblies, Ceglarek and Prakash [14] show a piecewise least squares approach for use in a state-space model. Their introduction reviews various publications in the field of fixture diagnosis methods. The force signature of the assembling robot arm is used by Rodriguez et al. as input to an SVM [82]. Luo et al. [61] extend this approach by abstracting specific behavior representations from the force signature.

3.1.5 Plant diagnosis

Diagnosis of production plants or machines can be realized by anomaly detection methods. In anomaly detection of production plants, one distinguishes between phenomenological and model-based approaches [70]. In phenomenological approaches, measurements are classified directly to detect anomalous behavior, while model-based approaches compare a system model representing the normal system behavior and the system's measurement data.

Due to the high amount of available publications, only a short introduction into the topic is given and the important topic of one-class classification is being skipped. For this, the authors would like to refer the interested reader to the comprehensive work of Shin et al. [96]. In case of phenomenological approaches, sensor data like time-series data is processed. To extract features from

it, transformations like wavelet transform [33], empirical mode decomposition [39, 117], or independent component analysis [101] are used. The features can be processed with various algorithms like ANN, SVM, optimizers, or fuzzy logic [127]. Typical applications are induction machines [8], pneumatic systems [27], gear boxes [86], and bearings [57]. Model-based approaches usually do not rely on feature extraction from time-series and can use machine learning algorithms like PCA or partial least squares [120] directly.

Closely related to anomaly detection methods, which are mostly used for failure detection, is the field of maintenance methods which aim to prevent machine failures due to deterioration of the machine. A distinction is made between time-based and condition-based maintenance, called preventive and predictive maintenance [66].

Preventive maintenance tries to extract the mean useful life of a machine and/or its parts to schedule maintenance activities before breakdown. To the author's knowledge, the use of machine learning methods for this task has not been reported to the scientific community yet, as simple statistics leads to good results [66]. For preventive maintenance, a mathematical formulation of the loss function to be optimized can be found (see, e.g., the work of Cassady and Kutanoglu [13]). If the term of preventive maintenance is abstracted to the level of job shop scheduling, the work of Adibi et al. shows parameter estimation by clustering [1], reinforcement learning [91], and ANN [2]. Predictive maintenance tries to extend the maintenance intervals by monitoring the machine's conditions, sparing costs for unnecessary, time-based scheduled, maintenance activities. In contrast to preventive maintenance, there are several authors applying machine learning methods in this field, and the authors like to refer the interested reader to the review of Ahmad and Kamaruddin comparing both time-based and condition-based maintenance for various examples [3].

3.2 Optimization with parameter changes

In order to optimize parameters of industrial processes which were described by machine learning methods, the typical workflow contains the following four steps [53]:

1. Generating a database with few experiments or run simulations with DOE methods,
2. Modeling the physical correlations between the process parameters and the quality criteria with statistical or machine learning methods,
3. Optimization of the process parameters using the created process model,
4. Adjusting the process parameters manually or automatically.

As mentioned in Section 2, the database for modelling the physical correlations with machine learning methods

can consist of measured data like in [46] or of simulated data [77, 103]. If the machine learning model is supposed to replace a time-consuming physics-based simulation, it is called a meta- or surrogate-model [78, 111]. With this method, the risk of error propagation through the different models is given. Both systematic and stochastic errors can occur during construction of the physics-based simulation and subsequently be adapted by the meta-model built from its calculations, resulting in an invalid meta-model as well. But even with valid physics- and meta-models, approximation errors to the real process have to be considered. However, the approaches discussed below are based on measured data. Often, the created process models are not simple linear regression models but complex non-linear models as SVM or ANN. The training of these models can be time consuming and computationally expensive, but for a good representation of the physical correlations, the usage of non-linear models is often indispensable.

The optimization of process parameters can be realized by traditional approaches like Newton's method, hill climbing algorithms, or gradient descent algorithms, leading to a local optimum. A second possibility to optimize the process parameters is to use evolutionary algorithms, usually leading to the global optimum of the given search domain. The usage of evolutionary techniques received a lot of attention in recent years [122, 123]. The approaches discussed in the following section use evolutionary algorithms in most cases.

3.2.1 Machine learning with subsequent optimization approaches

There exist a lot of different fields for machine learning approaches and subsequent parameter optimization. The following sections present examples in different specific manufacturing fields.

Milling Especially in milling processes, a lot of research was done on approaches including ANN and genetic algorithms (GA). The authors of [46, 97, 107] used these techniques to improve different quality criteria by optimizing the cutting parameters of the milling process. Denkena et al. [28] suggest a SVM to predict the geometric deviation of the workpiece. To optimize the cutting parameters, they were sampled on a grid and optimal parameters were chosen based on the prediction of the SVM. In [26], Coppel et al. compare ANN and SVM models to predict quality criteria and also test different optimization algorithms, such as GA, particle swarm optimization (PSO), and simulated annealing (SA) algorithms, respectively, to determine optimal cutting parameters for the milling operation. An ANN model with subsequent PSO achieved the best results.

Turning Turning operations were the process of interest in [9, 36]. In Bouacha and Terrab [9], an ANN with subsequent PSO was compared with a non-dominated sorting genetic algorithm (NSGA-II)-based RSM model. Because of less computation time, the ANN with PSO algorithm was the better choice in this case. Gupta et al. [36] used different modeling approaches like regression, RSM, SVM, and ANN to predict the quality criteria; GA was used to find optimal process parameters.

Gear hobbing and boring In the field of gear hobbing [12] ANN and in boring [108] ANN and SVR were proposed to predict the quality criteria. Cao et al. [12] optimized their process parameters based on ANN with a differential evolution algorithm. Venkata Rao and Murthy [108] used an unspecified multi-response optimizer.

Electrical discharge and abrasive waterjet machining The authors of [6, 62] have done research on parameter optimization in electrical discharge machining (EDM) and wire EDM [65, 79], respectively. All of them used ANN to predict the quality criteria, except Rao and Pawar [79], who applied a second-order regression model. The process parameters were optimized with different algorithms: augmented Lagrange multiplier algorithm [6], GA, PSO and SA algorithm [62], wolf pack algorithm based on the strategy of the leader (LWPA) [65], and artificial bee colony (ABC) algorithm [79]. In more special EDM, applications like wire EDM turning [55], micro-EDM [126], or micro-clearance electrolysis-assisted laser machining [104] parameter optimizations based on machine learned prediction models were conducted as well. All used more or less already mentioned combinations of ANN and NSGA-II [55], SVM and GA [126], and ANN and improved ant colony algorithm [104]. Zhang et al. [126] predicted the processing time and electrode wear with a support vector machine as a regression model. In the second step, they performed a multi-objective optimization with a GA. The results represent a pareto-optimal solution between the minimum processing time and minimum electrode wear. Srinivasu and Babu [100] and Zain et al. [124, 125] optimized the process parameters of abrasive waterjet machining with regression models and ANN, respectively, followed by GA.

Finishing For the parameter optimization process in roller grinding, Chen et al. [19] used RSM for the quality prediction and a hybrid PSO algorithm for the optimization task. For the optimal configuration of the grinding slurry of waterjet grinding, Liang et al. [58] used an adaptive neuro-fuzzy inference system (ANFIS) approach. Zhao et al. [128] optimized the parameters of the grinding and polishing

process of integrally bladed rotors by using a regression model and the signal to noise ratio for the optimization.

Plastic injection molding (PIM) and fused deposition modeling For PIM, extensive reviews are found in [31, 48], extending the possible methods to other meta-models and optimization algorithms. Further, authors like Chen et al. [18] and Xu and Yang [119] used ANN and GA or rather ANN, gray correlation analysis, PSO, and multi-objective PSO for the parameter optimization. Peng et al. [75] improved fused deposition modeling by using the response surface methodology combined with a fuzzy inference system and a GA optimization.

Welding In the field of welding, Rong et al. [83] proposed an extreme learning machine; Dhas and Kumanan [29], a quadratic regression model; and Norouzi et al. [71], an ANN, an ANFIS, and an ANN trained with PSO for predicting quality parameters. For process parameter optimization, Rong et al. used only PSO algorithm [83], while the other authors used both PSO and GA.

Others The last three examples for research in parameter optimization based on machine learning models are press hardening [103], electroplating [34], and selective laser sintering [84]. Stoll et al. [103] predicted their quality criteria with a linear regression model. In the second step, a parameter optimization based on the least squares method was performed. Genna et al. [34] and Rong-Ji et al. [84] predicted their quality criteria in electroplating and selective laser sintering with ANN and optimized the process parameters by a so-called external optimized algorithm and GA, respectively.

3.2.2 Machine learning with other optimization approaches

The previously mentioned papers contain various approaches to optimize process parameters and improve quality in many different manufacturing applications. In general, many researchers used ANN to describe their manufacturing process and predict the quality criterion of interest. In the second step, a GA was applied. Alternatively, the model and the optimization can be realized simultaneously by using an active DOE [94, 95], sequential approximate optimization [51, 52], or Bayesian optimization [20, 99, 102]. Another possibility is to inverse the problem. Instead of building a model and optimizing the input parameters, a model with quality parameters as inputs and process parameters as outputs is constructed [98]. This rejects the underlying assumption used beforehand that one specific parameter configuration will result in a defined quality value, but different parameter configurations can result in the same quality. Here, the assumption is

that different qualities can result from the same parameter configuration. This seems counterintuitive to the authors, but according to [98] the prediction error compared to experimental data is less than 5%.

4 Discussion and analysis

The reviewed literature shows that the production-related applications of machine learning with or without optimization are manifold. In this study, we investigated which combinations of production methods and machine learning models are most successful and how optimization methods for quality improvement can be integrated. Our results are presented in the following.

4.1 Classes and origin of used data

The available data for training the machine learning models can be classified according to the categories explained in Section 2: Process parameters mostly are on continuous scales, therefore most data in the mentioned papers contain quantitative data such as water pressure or jet traverse rate [100]. Further examples for interval and ratio data can be found in [116]. In a few cases, also nominal qualitative data are available, for example in [12, 16, 116].

Depending on the selected optimization goal, data can be available in the shape of time series and product-specific data. If the parameters are not changed during optimization (see Section 3.1), often only product-specific data are available, except in the area of anomaly detection [8, 27, 57, 86]. If the parameters are changed during optimization (see Section 3.2), the data may be available both as time series and as product-specific data. In the work of Bouacha and Terrab [9], among other things, the process forces and the surface roughness of the part are defined as outputs. Here, the process forces are available as time series and the surface roughness of the part as product-specific quantity.

For the distinction into controllable and uncontrollable data, as well as observable quantities and process state variables, it can be summarized that input variables are mostly controllable and observable quantities, for example: cutting speed [36] or electrode feed rate [104]. Input variables can also only be controlled indirectly, for example feed rates [26, 36]. The output variables, however, are mostly uncontrollable or only indirectly controllable, for example the process forces in Bouacha and Terrab [9].

Most of the data in the investigated papers was recorded and subsequently a machine learning model was trained. Exceptions are the work of Denkena et al. [28]; here, the model is further trained with present data. Furthermore, they also use simulated data to train the model. More examples of approaches based only on simulated data can be found in
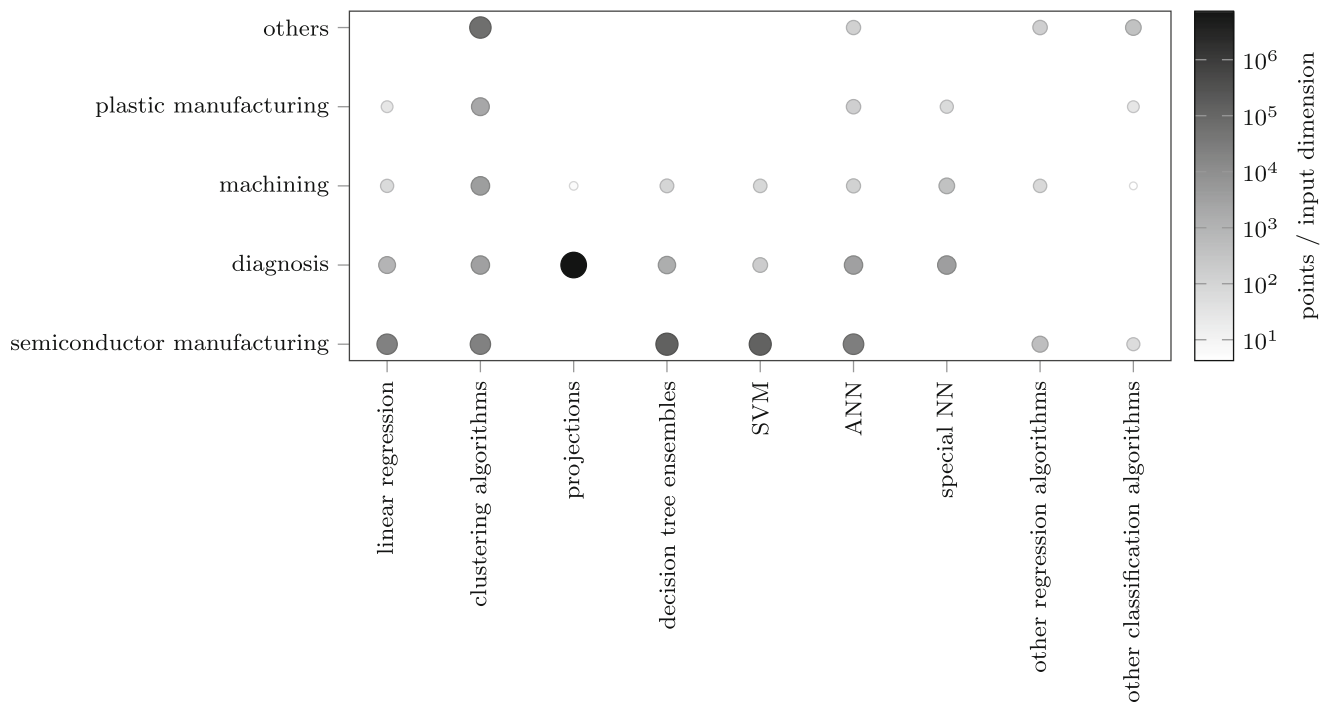
Fig. 1 Applications, algorithms, and number of data points per input. Size and color indicate the median of the number of data points per input dimension of the model. On the horizontal axis, the machine learning algorithms are roughly sorted by complexity

[51, 77, 103]. In the remaining articles, only measured data have been used.

4.2 Machine learning and applications

A closer look on the reviewed papers reveals several potentials to increase the effectiveness of machine learning for optimization of processes.

Figure 1 gives an overview of the analyzed research papers. Tables 1 and 2 map the different applications and algorithms to the classes used in Figs. 1 and 2.

It is obvious that in nearly every mentioned field of application every mentioned algorithm has been used. The size and color of the points additionally give a feeling for the used data. They represent the median of the number of data points per input dimension; the median is used due to the fact that the specific distributions are unequally distributed. It can be seen that most entries are on the same level, but there are upper outliers in semiconductor manufacturing and diagnosis, where huge databases are available.

To dive deeper into the topic of the used data and the model complexity, Fig. 2 shows the ratio of data points

Table 1 Classification of applications

Diagnosis	Machining	Plastic manufacturing	Others
Defect detection	Milling	PIM	welding
Automatic visual inspection	Welding	Fused deposition modeling	Gas forming
Assembly fault detection	Gear hobbing	Polyester film manufacturing	Press hardening
	Finishing		Job shop scheduling
	Drilling		Textile draping
	Turning		Deep drawing
	EDM		
	Abrasive waterjet machining		
	Boring		

Table 2 Classification of algorithms

Clustering	Projections	Decision tree ensembles	Special neural networks	Other classification algorithms	Other regression algorithms
kNN	PCA	Boosted trees	ANFIS	HMM	GLM
k-means	ICA	RF	CNN	Logistic regression	MARS
	Gabor filter		RBF-NN	Association rule mining	Regression tree
	SOM			Decision tree	Gaussian process
				Fuzzy classification	Extreme learning machine
				Statistical image processing	

per input dimension for different algorithms, sorted roughly by their complexity. Some really high ratios occurring in diagnosis via projections are skipped for a better scaling.

Two important points can be recognized from this figure. Firstly, the values of the data points per input dimension; secondly, the missing relationship of this ratio to the used algorithms.

The number of data points per input dimension varies between 1 and some thousand, and the authors like to state that ratios below 10 might be critical. To learn an appropriate model, the data has to represent the full complexity of the given process. For example, if the process is linear and assuming no noise, at least two data points
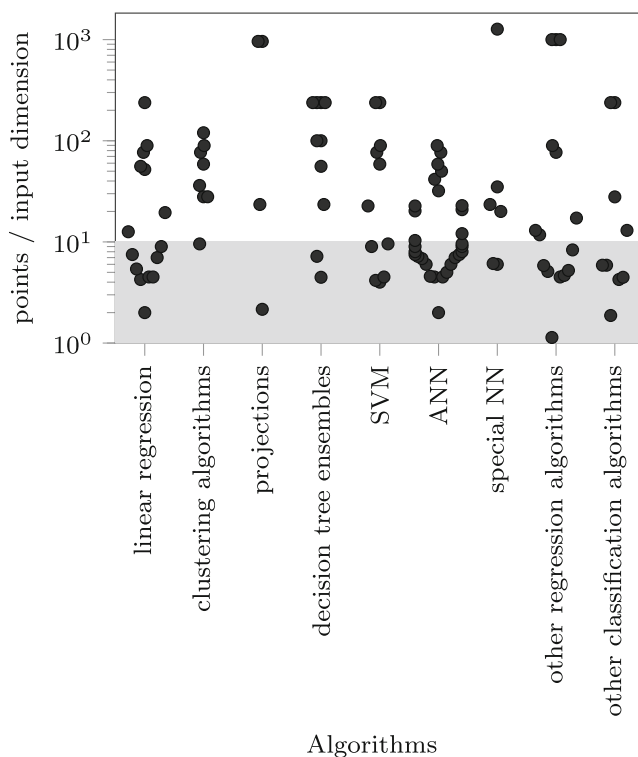
per dimension are necessary to map this relationship from the data. With increasing noise and the potential of outliers, the ratio has to increase as well to learn an appropriate model. As the industrial processes are assumed to have a higher complexity, it might be possible that even with a sophisticated DOE not all relevant relationships are represented by the data.

Relating the ratio to the algorithms, the authors expected them to be correlated, as a more complex algorithm that is able to map more complex relationships typically needs more representative data. But this expectation was not fulfilled, as there is no correlation visible. All algorithms are used with all possible ratios. In the opinion of the authors, this is considered critical. To stay with the example mentioned beforehand, an ANN can be used for a linear mapping as well as a simple linear regression, but the less complex model has several advantages over the ANN. On the one hand, it provides a better interpretability, so the mapped relationships can be understood and possible failures (of the data and the model) can be detected. On the other hand, a complex model needs more time for training, split into the actual training time, the feature engineering, and the tuning of the hyperparameters. If training time is an issue, this fact should not be ignored.

At the end of this paragraph, the authors want to point out that process complexity, the number of data points per input dimension to the model, and the model complexity are highly related. To learn an appropriate model, the data has to represent the process complexity and the model complexity has to fit both the process complexity and the number of data points available.

Fig. 2 Point-dimension ratio for used algorithms. The image was created using a swarm plot to make points with the same values distinguishable. The gray area indicates a critical amount of points per dimensions

4.3 Optimization algorithms

If optimization is used to find the best process parameters as stated in Section 3.2, an appropriate optimization algorithm has to be selected. As the loss function is assumed to be complex with different local optima, global optimization algorithms are used. In the meantime, GA is just as popular as PSO, while both approaches can provide similar results as comparisons like [29, 62, 71] show.

4.4 Applicability in the real process

In this section, the authors want to discuss the applicability of the different approaches in real production processes.

For root cause analysis, the early prediction of manufacturing outcomes, and diagnostic systems, approaches are assumed to work in real life (see e. g. [40, 44, 116]).

If process parameters are changed, the application is more critical, due to several reasons. Firstly, as the used data originates from simulations and experiments, it is not certain that it truly represents the real production process. Secondly, for a running process, optimization results have to be robust. They should be valid for different machines and products and should be able to tolerate measurement outliers like a crashed sensor. Thirdly, for process chains, certain parameter changes that are valid for a single machine might be inconvertible due to the relationship to previous and subsequent process steps. Processing times cannot change if the process chain shall not get out of step.

A more general problem seems to be the amount of available data, as the analysis in Section 4.2 shows. If that is the case, the authors propose to add additional, better available data such as simulation data or to inject knowledge using a gray box approach. Both possibilities can result in higher model accuracy and higher acceptance of the model. More data generally provides the ability to map more complex processes and to reduce the model's variance. With respect to the acceptance issue, the authors think that the opportunity to improve the model by domain knowledge can lower the hurdle to use it. Together with an interpretable model like the rule mining approach by Kamsu-Foguem et al. [44], this can help establish appropriate data mining approaches for optimization in production.

5 Conclusion and further aspects

5.1 Summary

The advent of smart manufacturing simplifies the exploitation of data provided by whole production plants, individual machines, or single sensors, enabling machine learning at different stages of complexity. Simultaneously, a shortage of resources and the struggle of manufacturers to stay competitive makes machine learning necessary to spare energy, time, and resources and to reduce waste. As data often already exists in various storages or is cheap to create, the step to its beneficial use is a small one.

In this review, the available data types and the use of the data for machine learning in different applications were described. The applications vary from the simple setting of learning a valid machine learning model to the combination of machine learning with optimization. If only a model is learned, it can be used for root cause analysis, the early prediction of manufacturing outcomes, and diagnostic systems to optimize product quality or process efficiency. Else, if a model is combined with optimization algorithms, it is possible to find production parameters optimal for a specified loss function. This function can include the mentioned constraints on energy, time, and resources and waste or describe a specific measure of the part's quality. The optimized parameters and their introduction into the machine make the whole production process more flexible and adaptive to the different requirements occurring in the process.

5.2 Conclusion

Given these potentials of optimization, the closer analysis of the overall process of data collection, model training, and optimization revealed a critical aspect: the connection between the process complexity, the stored data amount, and the model complexity. In the inspected papers, quite often, this connection was not respected, leading to complex models being trained on low amounts of data, risking overfitting and/or a lack of interpretability. This aspect can gain skepticism toward the application of machine learning in the manufacturing industry. To face this challenge, the authors recommend being careful in every step of building the optimization chain and to question the data, the used machine learning methods, and optimizers. Other critical aspects hindering the optimization of processes via machine learning might be a lack of relevant data or difficulties in getting access to the machine's control systems. All these problems might vanish with time passing to gain expertise, fill storages, and lower hurdles by hard- and software.

5.3 Future research directions

In the author's eyes, machine learning in production is not limited to the before-mentioned improvements. It has the specific chance to improve product quality enormously if applied for open-loop control for multi-stage production processes, as already proposed by Konrad et al. [54], Lieber et al. [59], and Arif et al. [5]. As product quality can already be predicted at early production stages as done by Weiss et al. [116], one could optimize for the best subsequent machine parameter set to achieve the best possible product quality, given the limits of the raw material, the production parameters, and the previous processing results. Thinking bigger, this approach could be extended from the product-specific stage to machine- and plant-specific stages, improving the overall efficiency taking resource, energy, and time restrictions into account.

Yet another future research topic could be the simplification of machines and the use of larger tolerances of the raw material. Machine learning–based optimization techniques might face the higher requirements of the processing steps, ensuring unvarying quality, and simultaneously reducing the costs of machines and the raw material.

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