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Systematic review on machine learning (ML) methods for manufacturing processes – Identifying artificial intelligence (AI) methods for field application

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Abstract

Artificial Intelligence (AI) and especially machine learning (ML) become increasingly more frequently applicable in factory operations. This paper presents a systematic review of today's applications of ML techniques in the factory environment. The utilization of ML methods related to manufacturing process planning and control, predictive maintenance, quality control, in situ process control and optimization, logistics, robotics, assistance and learning systems for shopfloor employees are being analyzed. Moreover, an overview of ML training concepts in learning factories is given. Furthermore, these concepts will be analyzed regarding the implemented ML method. Finally, research gaps are identified.

1. Introduction

There are several reviews of the use of machine learning/ data mining or other AI implementations for former years, for example HARDING ET AL. who give an overview of artificial intelligence applications from 1987 to 2005[1–6]. The trend for AI and especially ML is still unbroken and is further increased by the rising trend in digitalization. Current competitions on the web (e.g. Kaggle.com) show, that companies see huge potential in data driven techniques and are willing to grant big prize money for the best solutions to solve specific problems [7–9]. Referring to GOODFELLOW, the true usage of AI is to solve problems that are hardly or not at all formulated into code but can only be solved intuitively [10]. Machine learning (ML) is one subset of AI and its usage only recently shifted from research to industrial applications, as this article shows. With the ongoing process of digitalization in industry comes growing data and thus growing datasets which a ML application can use

to gain knowledge from historical events. Especially Deep learning (DL), a subfield of ML and AI and their applications in form of convolutional neural networks (CNN) and other deep neural network (NN) architectures proved to be effective for specific applications such as image recognition or object detection problems (e.g. [11],[12]). To structure the former mentioned shift from research-only solutions to applications in the factory environment from year 2015 ongoing, this article gives a systematic review of several fields and occurring examples of application.

Nomenclature	
AI	Artificial intelligence
ML	Machine learning
DL	Deep learning
CNN	Convolutional neural networks
NN	Neural Network
SLR	Systematic Literature Review

SVM	Support vector machine
KNN	K-nearest neighbour
RF	Random Forest
MLP	Multilayer perceptron
GBT	Gradient boosted trees

2. Structured review methodology

For reviewing literature the standard systematic literature review (SLR) method was used, by employing a manual search of three databases. The guidelines which were consired for this review are based on KITCHENHAM ET AL. [13] The SLR therefore follows the structure of defining the research question, determining required characteristics that are being focused on, a selction of pertinent literature and a conclusion where the insights are synthesized and reported. Starting, the research question of the conducted structured review is as stated: *Finding deployed applications of machine learning in the factory environment of the last five years*. As a further additional condition, the following manufacturing applications: manufacturing process planning, quality control, predictive maintenance, logistics, robotics, assistance and learning systems, ML-training concepts in learning factories and process control and optimization were selected as primary focus within a typical factory or especially learning factory environment. Every paper is summarized and, if possible, the deployed and/ or used algorithm for solving the specific issue is stated.

Published works from industry and research are reviewed and analyzed. Moreover, this article focuses on actual implementations of AI/ ML and does not consider conceptual or methodical papers without a proper implementation or description of the used algorithm.

The structured review proceeds as followed: the earlier mentioned subtopics are used for a keyword search in combination with keywords referring to the "manufacturing" and "factory" domain. All relevant papers and publications were scanned regarding actual implementations of AI techniques with a focus on ML applications. The remaining papers were then summarized and analyzed regarding their use of ML applications and an overview is given in Table 1.

Table 1. Overview of applications and algorithms.

Subtopic	Application	Algorithm	Literature
Manufacturing process planning	Scheduling	Q-learning, RF, decision tree	14,15
	Cost & energy prediction	NN, SVR, GBT, RF, others	16,17,19
	System modeling	log. Regr., RF, decision tree, bayes	18
Quality control	Quality cost reduction	decision tree, NN, SVM, others	11,12,20, 21
	Process line quality	Decision tree, Bayesian network	22,23,24, 25
Predictive maintenance	remaining useful life &	Decision tree, NN, PCA, KNN, others	26,27,28, 29
Logistics	Scheduling	NN, Q-learning, deep q-learning, RF	30, 31,32, 34
Robotics	Human robot collaboration	hidden markov model, KNN, clustering, NN	35,36,37, 38,39
	Path planning	KNN, NN	38,43
	other	NN, deep p-network	40,41,42
Assistance and learning systems	assembly assistance	NN	48
AI-training concepts in learning factories	Object-Recognition	NN	50
Process control & optimization	Production line	GBT	8,9
	Process and tool condition forecast	NN, trees, RF, SVM, mult. Regr., others	55,56,57, 58
	other	NN, SVM, KNN, others	51,52,53, 54

3. ML-Summary

ML can be divided into three subtopics: supervised learning, unsupervised learning and reinforcement learning. The findings of the article depicted in Fig. 1 present, that the majority of ML methods used are supervised methods. Moreover, Fig. 1 shows, that in recent years in a variety of architectures NN are used to solve challenges in the manufacturing domain followed by tree algorithms.
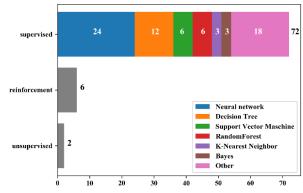

Fig. 1: Used methods for applications of the structured review

NN are models consisting of nodes, weigths and layers and are intended to mimic a learning approach similar to the brain. Whereas tree algorithms are architectures with branches that inherit information about an item, up to its leaves which contain the target of the regarded item. Besides models from supervised learning, there are techniques from unsupervised learning such as singular value decomposition and principal component analysis that can be used to reduce the dimension of the data. A popular algorithm for reinforcement learning though is Q-learning where agents try to learn the best strategy regarding a specific cost-function for possible acitons that can be performed. Further descriptions of the mentioned models and alghorithms are not in the scope of this article and can therefore

be found in current literature, for example GOODFELLOW ET AL. [10]. Future work will address this by analyzing the use of each model for the presented topics at hand.

4. Factory-Applications

In the following, the mentioned subtopics will be examined regarding the usage of ML applications in the context of factories. The presented papers are summarized shortly as a further description of all papers cannot be done due to structural limitations of the paper. Yet, all papers were analyzed in depth and are referenced for further interested.

4.1. Manufacturing process planning

Scheduling problems are one big topic in the field of manufacturing process planning. There are several approaches of solving those with the use of ML tools. KIM ET AL. utilize Q-learning to schedule data packages in an IOT scenario where a large amount of data is produced by different sensor nodes [14]. Another scheduling problem stated as a reentrant flow-shop problem is published by LUBOSCH ET AL. The approach consists of a combination of random search algorithms combined with machine learning algorithms [15].

A cost prediction for future production of jet engine blades is modeled using multiple linear regression, generalized additive models, NN, SVR and GBT by LOYER ET AL. Their findings show that, for this particular problem, SVR and GBT were superior to NN and multiple linear regression [16]. RENTSCH ET AL. implemented a fitness function and genetic algorithm for a parameter optimization for energy and resource efficient manufacturing chain design and operation [17]. BRIK ET AL. utilize supervised methods such as a RF, logistic regression, gaussian naïve bayes and a decision tree for the classification of workers' localization in a system disruption model. The algorithms are selected not only comparing the metric of classification accuracy but also taking into account prediction time and modelling time [18]. Forecasting the load of the research factory 15 minutes in advance is done by WALTHER ET AL. using extremely randomized trees, RF and GBT. In a first step, feature selection is performed using a model-based feature selection and a recursive feature elimination technique before hyperparameter tuning of the chosen algorithms is performed. WALTHER ET AL. End their implementation with a specific feature engineering utilizing moving averages to further increase the performance of the conclusively chosen algorithm [19].

4.2. Quality control

The following implementations and publications all refer to the problem of reducing quality assurance costs. For example, HUBER ET AL. use a decision tree for the optical classification of battery separator defects [20]. Another optical inspection for blister defect detection for lithium-ion batteries is performed by MA ET AL. In contrast to the former used decision tree approach, MA ET AL. use a CNN, more precisely a DenseNet architecture. This architecture is improved by adding trainable parameters in the dense block of the CNN. In an evaluation, the proposed CNN architecture is compared to other algorithms (NN, SVM, support tucker machine, other deep neural network architectures [11]. Further, LAVRIK ET AL. optimized the optical quality assurance of silicon sensors using a different deep neural network architecture called Faster R-CNN gaining good results in their publication [12]. Yet another problem with regard to optical quality is dealt with by STAAR ET AL. The publication proposes a new triplet architecture for CNN because the specific problem inherits a possible endless amount of target classes which the authors have to face. To overcome this challenge, two data augmentation methods are applied and the algorithm is trained on three different datasets to improve accuracy [21].

A different topic in contrast to the former optical quality detection is faced by PACHNER ET AL. and LOKRANTZ ET AL. Both focus more on a whole production process than on a final visual inspection to implement ML as a solution. LOKRANTZ ET AL. model a Bayesian network to identify the root cause for quality deviations in two different manufacturing processes. A key finding is the relevance of expert knowledge to pose a model for manufacturing processes as a Bayesian network [22]. However, PACHNER ET AL. model a decision tree to gain insights about the influence of several process parameters on the floss of the final product for the optimized manufacturing process of powder coating [23]. Further, an analytical approach using a decision tree algorithm (C4.5) to improve classification results in an end-of-line testing of an automotive manufacturer [24].

Yet, an entirely new field is faced by SUMESH ET AL. with their implementation of a RF and a decision tree (J48) for the quality classification of a welding process. During their analysis, the RF reached classification rates of up to 88.69% and J48 rates of 70.78% and suggestions are given to further increase the algorithms in future implementations [25].

4.3. Predictive maintenance

Predictive maintenance and its subdomain of predicting the remaining useful lifetime are frequently published topics and are often named as prime examples for the usefulness of digitalization. PINTO ET AL. make use of unsupervised and supervised methods such as PCA, survival analysis, KNN, CNN and extremely randomized trees to implement a fault detection and estimate the remaining life for robots [26]. A combination of a statistical model designed with probability density functions and a machine learning model using further sensor data to estimate the remaining useful life for industrial equipment is published by KRAUS ET FEUERRIEGEL. They propose a new NN architecture named structured-effect neural network combining the advantages of both approaches [27]. Another predictive model is built by Scalabrini Sampaio et al. utilizing a NN. Their setup consists of a computer cooling fan with several magnets attached to the fan to build a dataset for typical motor vibrations [28]. Another implementation is done using logistic regression for IoT sensor data by IBM. Equipment failure is modelled in IBM's Watson Studio [29].

4.4. Logistics

Scheduling problems are also trending in the field of logistics. KUHNLE ET AL. implement a reinforcement implementation utilizing NN for order dispatching using tensorforce. The state representation, reward function and hyperparameters are described in detail. Moreover, their publications explicitly address engineers who are not familiar with ML and/or especially reinforcement learning [30]. A similar approach is published by SHIUE ET AL. for job scheduling in a smart factory. SHIUE ET AL. model a real-time scheduling problem with reinforcement learning using Q-learning. The implementation is compared to a self-organizing map neural network, a single dispatching rule approach and heuristic rules and outperforms those approaches [31]. A third scheduling problem is approached by WASCHNEK ET AL. by implementing googles deep mind DQN Q-learning algorithm to solve a production scheduling problem in a simulated semiconductor production facility. The problem is stated as a markov decision process and a NN is trained to predict the action and on top of this prediction there is the reinforcement learning algorithm in form of DQN algorithm to correlate decisions with rewards to improve actions [32].

KNOLL ET AL. published to predict logistics using machine learning and mathematical models to form a mixed model for prediction [33]. Further, KNOLL ET AL. implemented a RF for packaging in logistics using 11 features to model not only a classification but also a regression task. Classification accuracies up to 84% are published and further feature importance is analyzed [34].

4.5. Robotics

Robotics offer a wide variety of applications for machine learning and AI technologies for automation and Human robot collaborations. For human robot collaboration there is an urgent need to keep the human safe while working with a robot. That is why DUCKWORTH ET AL. propose an approach using unsupervised learning methods such as Latent Semantic Analysis and Single Value Decomposition to transform human motions into lower dimensional data. In a second step, DUCKWORTH ET AL. use a state of the art CNN (OpenNI) for 2D human pose estimation and comparing their supervised and unsupervised approaches [35]. Another approach is proposed by TOURLOMOUSIS ET AL. who use a pretrained VGG16 architecture and added a LSTM-Layer at the end to improve the model even further, naming it the Improved Motion Recognition and Prediction Network. In this structure, the CNN works as a feature extractor and the LSTM-layer is used to extract temporal patterns. They validate their approach in a desktop assembly use case with up to 83% motion recognition [36]. Yet, only LIU ET AL. utilize a hidden markov model to predict human motions in a collaborative engine assembly use instead of a NN solution [37]. In Contrast to the former use case applications, DRÖDER ET AL. developed an experimental simulation platform for human robot interaction. Including path planning making use of a KNN and clustering analysis and object detection using a feed forward NN [38]. Not predicting

human motions but evaluating safety zones with an implementation of the OpenPose library based on a CNN structure. The data is further enhanced with depth information to reconstruct human motion in an environment [39].

A general object recognition approach is proposed by CHEN ET AL. based on the Faster R-CNN structure applied to a gripping application [40]. An innovative way to interact with robots and their graphical user interface is published by KUHNER ET AL. The implementation works based on two retrained CNN on EEG data to operate a graphical user interface for mobile robotic service assistance by thought [41].

To improve automation tasks, TSURUMINE ET AL. published a deep reinforcement learning approach to teach a robot how to flip a handkerchief and fold a t-shirt. The utilized algorithms are a deep p-network and a dueling deep p-network, reaching better results than previous methods [42].

Lastly, YIN ET AL. train a NN in combination with a swarm intelligence based algorithm to face the challenge of energy efficient path planning for robotic applications [43].

4.6. Assistance and learning systems

Both CHAN ET AL. as well as HERRMANN ET AL. state that AI has the potential to support and enhance the capabilities of employees (e.g. [44,45]). So beyond the sphere of machine-based problems, AI can be valuable to support the competence and knowledge management of employees. The two key aspects for the assistance of employees are the guidance of individual learning processes [46] and the control of competences saturation [47] within the production system. Although there seems to be a great potential to support workers in manufacturing processes most of the research is focused on cognitive assistance systems. HALSGRÜBLER ET AL. propose a framework for supporting workers in semi-manual tasks to insure high quality products with no defects. They state that the system using NN is able to give instructions based on the performed skill of the worker [48]. REISINGER ET AL. show research concepts for automated digital assistance system (DAS). Also focusing on assembly tasks the proposed concepts states the need of interconnections of different programs e.g. 3D-CAD, media generator [49]. With only one actual implementation by HALSGRÜBLER ET AL. this section is considered as a gap of research.

4.7. ML-training concepts in learning factories

Training concepts in learning factories have been increasing over the past decade. But the topic of ML has not been a focus of teaching and learning within a real world manufacturing environment. One publication was found using an assembly environment on the shopfloor to teach the implantation and application of ML to workers or students [50]. Thus leaving it as a gap of research.

4.8. Process control and optimization

In the field of process control and optimization, a diverse landscape of ML applications can be found. Bosch started a Kaggle competition addressing the problem of a production line monitoring where 1373 teams participated. Bosch provided a training and test set of anonymized features of its production line. Many published solutions (1st, 3rd and 7th) for this monitoring were based on the implementation of GBT (XGBoost, LightGBM) by achieving a Matthews Correlation coefficient of more than 0.511 [8].

Mercedes Benz started another Kaggle competition in 2017 challenging the public to reduce the time for each car spending on the test bench. The best and second best solutions were published. The winning solution used GBT (XGBoost) again and the second solution used an ensemble of different algorithms consisting of Gradient Boosting Regressor, RandomForestRegressor, and a Support Vector Regressor, both solutions having R2-Scores > 0.55 [9].

DU PREEZ ET OOSTHUIZEN give a great comprehension for machine learning applications regarding cutting processes. Their study shows that most commonly used algorithms are NN followed by genetic algorithms, response surface methodology and particle swarm optimization [51].

A comprehensive three step approach for laser welding is published by GÜNTHER ET AL. It consists of an auto-encoder for feature extraction in the first step, a general-value-function learner on top of those extracted features, finalized by a reinforcement learning implementation to improve found strategies and policies. Tests using a SVM show, that the extracted features of the NN were more useful than unsupervised methods for dimensionality reduction such as a principal component analysis for their application in laser welding [52].

Another application of a multilayer feed forward network with backpropagation is implemented by OPRITESCU ET VOLK to deliver manufacturing strategies for different part shapes [53]. From incremental metal forming to selective laser melting, UHLMANN ET AL. present an implementation of KNN, Bayes classifier, NN and SVM to analyze best process parameters. Gaining best results by utilizing a bayes classifier and clustering to find groups with patterns in the data [54].

Regression and forecasting applications are common in this field as well. One is published by HWANG ET AL. where a regression of the temperature of an oven is implemented using a sequence-to-sequence model to predict future temperatures [55]. Not predicting temperature but control states of a manufacturing system is done by VAZAN ET AL. using NN, Tree algorithms, RF, multivariate adaptive regressions splines, SVM and multiple regression. By using the different algorithms and testing those against each other VAZAN ET AL. use the outputs to forecast the manufacturing system verified on a simulation model [56]. KÜFNER ET AL. focus more on a single machine classifying process states using a NN in form of a MLP [57]. Last, SOSSENHEIMER ET AL. use multivariate linear regression, NN and mean value calculation to propose several approaches for different digitalization standards for a condition-based energy monitoring of a machine tool [58].

5. Conclusion

The SLR at hand analyzed the current state of the art of recent years (2015-2020) with a strong focus on actual implementations and direct naming of used machine learning algorithms in the factory environment for each literature.

All in all, diverse applications are published using those technologies, thereby enhancing industrial solutions. Figure 1 sums up the used ML models used for the applications found in the SLR at hand. It is apparent that the use of NN and decision tree algorithms is widely used in manufacturing and factory applications during past five years. As for the used machine learning method, supervised methods dominate the state of the art with reinforcement learning methods gaining more attention in the last two to three years. The fact that unsupervised methods are only mentioned twice might be due to the fact, that the actual data preparation and exploration were not described as detailed as the implemented regression or classification task in many publications. The authors are of the opinion that way more implementations make use of unsupervised methods along the whole data analysis pipeline even though they are not mentioned explicitly.

As a result of this paper, two major gaps in research were revealed, shown by the very few to none existing paper on the topics of assistance systems and learning factory training concepts. Although assistance systems have been the focus of research for the past years the implementation of ML to these systems has not been mentioned in literature. With ML becoming more relevant for manufacturing processes the skills of workers and experts within the factory towards ML have to be developed. Since learning factories are an ideal environment to train workers, experts and students new training concepts have to be developed for training the application and implementation of ML. In our further research we will investiage the suitability of the listed algorithms (Table 1, column 3) for use in the respective application. .

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