publish-Ing.

Journal of Production Systems and Logistics
Volume 2 | Article 1
Published: January 2022

Identification and Analysis of Patterns of Machine Learning Systems in the Connected, Adaptive Production

Günther Schuh[1], Paul Scholz[2], Johannes Portik[2]

[1] *Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany*
[2] *Fraunhofer-Institute for Production Technology (IPT), RWTH Aachen University, Aachen, Germany*

Abstract

Over the past six decades, many companies have discovered the potential of computer-controlled systems in the manufacturing industry. Overall, digitization can be identified as one of the main drivers of cost reduction in the manufacturing industry. However, recent advances in Artificial Intelligence indicate that there is still untapped potential in the use and analysis of data in industry. Many reports and surveys indicate that machine learning solutions are slowly adapted and that the process of implementation is decelerated by inefficiencies. The goal of this paper is the systematic analysis of successfully implemented machine learning solutions in manufacturing as well as the derivation of a more efficient implementation approach. For this, three use cases have been identified for in-depth analysis and a framework for systematic comparisons between differently implemented solutions is developed. In all three use cases it is possible to derive implementation patterns as well as to identify key variables which determine the success of implementation. The identified patterns show that similar machine learning problems within the same use case can be solved with similar solutions. The results provide a heuristic for future implementation attempts tackling problems of similar nature.

Keywords

machine learning; production; algorithm selection; implementation strategy; connected production; Industry 4.0; learning systems

1. Introduction

In the past six decades, many companies have discovered the potential of computerized systems in the manufacturing industry. In the field of machine tools, for example, computerized numerical control (CNC) enables higher precision machining of more complex workpiece geometry and high repeatability of the achieved result [1]. Looking at the overall production facility, computer control of the equipment enables a significantly reduced production time of new components [1, 2]. At the same time, the introduction of computer-aided design (CAD), computer-aided manufacturing (CAM), and computer-aided quality (CAQ), among others, led to a reduction in time-to-market of up to 50% [1]. Hence, during the last decades digitization can be identified as one of the main drivers of cost reduction in the entire manufacturing industry.

Another advantageous side effect of digitization is the increasing generation of new data. For example, many sensors are installed in today's production machines to allow a more precise control of the machines. The hereby generated process data harbors the still largely untapped potential e.g., to make predictions about

This Paper has been reviewed by the Certified Reviewer Community of publish-Ing. – 1 review – double blind

DOI: https://doi.org/10.15488/11626
ISSN: 2702-2587

component quality during the process. The analysis of the recorded process and machine data can enable measures to improve, for example, component quality, throughput time and manufacturing costs. Furthermore, the complete automation of complex tasks, e.g. dynamic order planning based on the measured real-time data by algorithms, is conceivable. [3]

Despite the advantages of advanced data processing, the technical realization of it is not trivial. Traditional approaches of developing algorithms, which are based on imperative programming methods, are not target-oriented due to the increasingly complex challenges of the connected adaptive production (CAP) [4]. Firstly, the collected data is often of unstructured nature, i.e. the data sources may vary in the recorded format, in the accuracy of the measurement, or in the unit [5]. Secondly, the large number of sensors within a machine leads to a very high dimensionality of the data set [5]. This can lead to problems in the calculation of standard computational operations. Uncovering the insights inherent in the data thus requires a novel approach to programming algorithms.

Machine Learning (ML) methods offer the potential to circumvent problems of traditional programming [6]. The use of ML has three main advantages over classical methods of programming and is consequently promising to exploit in the CAP: [7]

1. the ability to recognize complex relationships and uncover previously hidden causalities [6, 8],
2. to adapt to dynamic environmental conditions [3, 6],
3. to continuously improve analysis results [6, 9].

Although the general potential of ML is well known and the methods of ML are very well understood and described scientifically, the transfer to real applications is slow. According to a survey 2019 conducted by CAPGEMINI, the percentage of automotive companies using ML on a large scale is only 10% [10]. Although there are several successful pilot projects in industry, companies do not recognize all relevant fields of action of this technology [10, 11].

A possible cause of the slow adoption of Machine Learning Systems (MLS) is the difficulty in selecting the best algorithm and systematic data preparation [6]. Moreover, managers' and employees' lack of experience hinders the development and efficient use of MLS [11]. Currently, this leads to high inefficiencies in several following dimensions in the industry. Developing new MLS without a systematic approach leads to temporal inefficiencies. An operational MLS created through a trial-and-error approach may not be optimal and results in technological inefficiencies. Failure to replicate operational MLS or to take advantage of synergies in developing new MLS leads to systemic inefficiencies. Finally, companies overlook relevant new fields of application of the technology due to a lack of knowledge of the technological potentials, which can be described as organizational inefficiency. [11, 12]

Therefore, this paper seeks to overcome the inefficiencies described above and to simplify the future identification and design process of MLS. Furthermore, this research aims to minimize the dimensions of possible inefficiencies mentioned in the previous section. For this reason, the goal of this paper is to identify successfully implemented MLS, to analyze them with respect to their implemented data analytics technologies, and to derive an implementation heuristic for new implementation endeavors in the CAP.

For this, the paper is structured in six parts. Firstly, an initial hypothesis is formulated based on underlying physical properties. Secondly, a literature review is conducted. Thirdly, the relevant theoretical background knowledge is summarized based on the literature review. The methodological approach is outlined, and the results are derived in the following. Lastly, the results are discussed, and an outlook is given.

2. Hypothesis

As outlined in Chapter I, the manufacturing industry is only slowly adopting ML solutions, despite their identified potential [10, 11]. As a direct consequence, this hinders established companies with mechanical engineering background to stay competitive and leaves cost reduction potentials unrealized [10]. Therefore, the industry is in need of a more efficient implementation approach which factors in and leverages knowledge of successfully implemented MLS [13].

A working MLS can be very complex and tailored to serve a specific purpose on a specific machine [6]. The "no-free-lunch theorem" states that "the only way one [algorithm] can outperform another is if it is specialized to the structure of the specific problem" [13]. From this, it can be hypothesized that similar MLS consist of similar building blocks that together constitute a pattern. Following this idea, a "divide and conquer" approach seems promising. For example, one popular problem is to predict the workpiece quality from sensor data of a CNC machine [3, 14]. Similar processes have similar underlying physical interrelationships and therefore similar data patterns on an abstract level [15, 16]. For this reason, it should be possible to tackle similar problems with a similar solution approach. Formulated more specifically to the given context, it should be possible to take existing solutions of MLS and "copy plus adapt" them to similar tasks, resulting in an efficient replication and implementation of new MLS. This hypothesis will be examined in the following chapters.

3. Literature Review

Following the hypothesis of the previous chapter, building blocks of MLS must be identified. For this reason, existing literature is analyzed to derive these MLS building blocks – in the following also referred to as characteristic components. The characteristic components of MLS are then used to derive a framework, which allows for a systematic comparison of different working MLS solutions as well as the search for patterns.

The analysis of existing literature is divided into two parts: the object area and the target area. The object area is focusing on literature which is a necessary foundation of this paper. The analysis of the target area focusses on topics that are helpful to achieve the overall goal of this paper. Following this differentiation, the *characteristic components of MLS* as well as *key areas, challenges, and untapped potential in the CAP* lay the foundation for this paper. Respectively, the dimensions of the target area are the *definition of a framework for the systematic analysis of different working MLS solutions* as well as the *derivation of patterns of working MLS solutions for given use cases*. Figure 1 evaluates existing approaches from literature with respect to the dimensions of the object- and target area. Hereby the degree of fulfillment is indicated by Harvey balls.

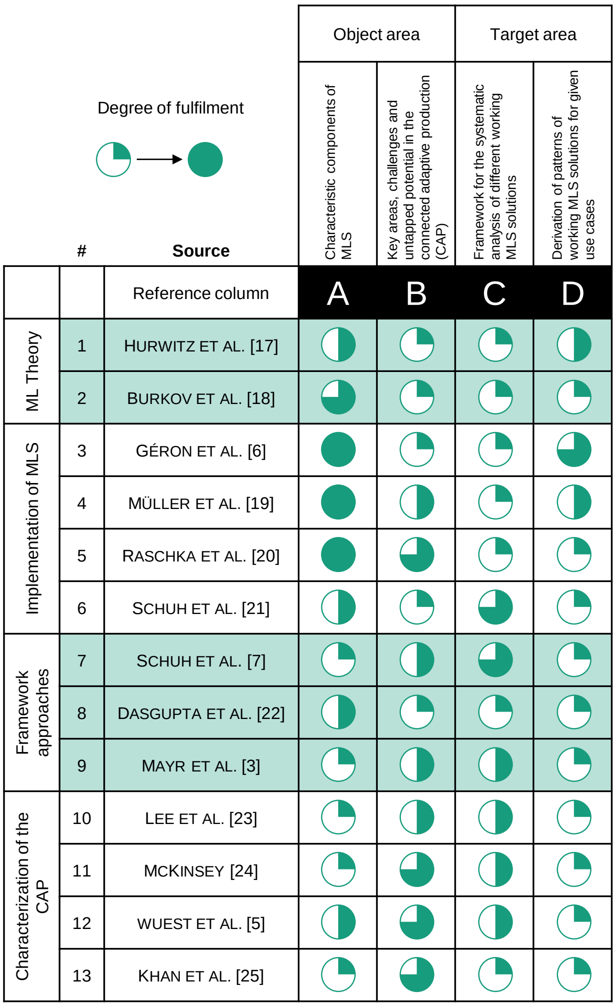

Figure 1: Analysis of existing literature (split into object area and target area)
[17, 18, 6, 19–21, 7, 22, 3, 23, 24, 5, 25]

Figure 1 shows that the fundamentals of ML, including basic approaches to implement MLS, are well understood and described in literature (cf. A1-A5). The functionalities of different ML algorithms are explained as well as optimal data model properties are presented. Especially the works of GÉRON ET AL. and MÜLLER ET AL. focus the implementation of individual algorithms [6, 19]. The implementation focus is beneficial for this paper as several characteristic components of practical projects are discussed. In summary, the basic approach to MLS implementation is described. Nevertheless, each problem's individuality still is a challenge. Often, this leads to implementation inefficiencies in practical endeavors.

The second object area (*key areas and challenges and untapped potential in the CAP*) is satisfactorily characterized in the analyzed literature (cf. B10-B13). While different publications focus on different aspects of challenges in the CAP, the overall results can be considered as sufficient for the purpose of this paper. In detail, this means that key challenges of the CAP are identified and areas of untapped potential are identified (e.g. quality prediction, wear prediction, and production planning). Furthermore, the complexity of the manufacturing processes and the unstructured nature of the recorded process data are highlighted as challenges.

Regarding the target area's dimension *definition of a systematic framework* the framework of SCHUH ET AL. is to be highlighted, as several dimensions of the analysis are systematically elaborated [7]. However, no dimension in the framework proposed by the authors relates to data properties or performance metrics. As stated in the works of BURKOV ET AL. and MÜLLER ET AL., data properties of MLS have a great impact on their solution potential [18, 19]. Therefore, the framework presented by SCHUH ET AL. is not optimal for this paper. Many other publications present (often only specifically useful) characteristic components of MLS (cf. C2-C12). Therefore, while many approaches in the existing literature provide elements of a framework, this first dimension of the target area is considered as not fully covered by existing literature and a refined framework must be developed.

The *derivation of patterns of MLS solutions* as the second category of the target area builds upon the first as a systematic framework has to be utilized in order to enable the search for patterns. Since no systematic framework is defined, consequently the derivation of patterns cannot be regarded as completely fulfilled either (cf. D6-D9).

Based on the above analysis two main research deficits are derived. Firstly, existing literature lacks a complete and standardized framework. The framework of SCHUH ET AL. e.g., lacks characteristic data properties and performance metrics. Secondly, patterns of working MLS solutions have not been derived in existing literature. Following the hypothesis stated in Chapter II that similar problems can be tackled by similar solution approaches, working MLS solutions have to be analyzed for patterns which then can be transferred to similar problems.

4. Theoretical Background

As mentioned previously, the framework of SCHUH ET AL. as well as other characteristic components are essential to the goal of this paper. Taken together, these characteristic components can form a framework useful to compare differently implemented MLS. The necessity for additional framework elements arises from the following: Some implementation variables (not mentioned by SCHUH ET AL.), e.g. the data set size, can be cost drivers in real-world applications and are therefore of interest [26].

4.1 Framework of SCHUH ET AL. [7, 21].

SCHUH ET AL. derive a framework for the systematic description of MLS and use it exemplarily for an analysis of a MLS [7, 21]. In the following, the framework and its core elements are presented briefly.

The upper part of the framework serves to visualize the diverse influences and backgrounds of Artificial Intelligence (AI). Likewise, the research area of ML is classified into that of AI. SCHUH ET AL. identify the following dimensions to enable a systematic comparison of MLS [7, 21]: ML strategy, ML goal, ML implementation procedure, ML algorithm. According to Figure 2, each of the dimensions presented can have one expression only. The individuality of a single MLS is abstracted by using the framework. The specific combination of the characteristics of all dimensions thus form a unique path and enable a systematic comparability of different MLS.

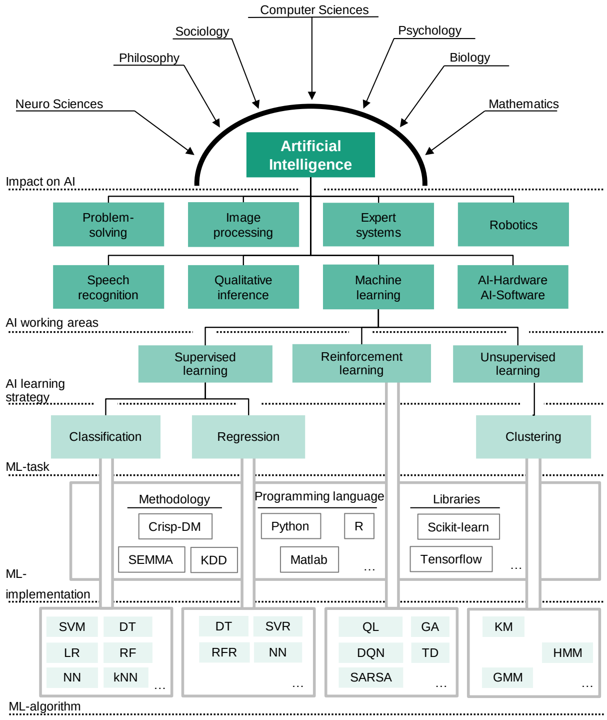

Figure 2: Framework proposed by SCHUH ET AL. [21] (Legend: Please refer to paper by SCHUH ET AL. [21])

4.2 Characteristic components by WUEST ET AL. [5]

The importance of the acquired data is highlighted in literature. Challenges are both the relevance of the data and the most optimal representation of the ingested data within a data model. WUEST ET AL. identify several characteristic components of MLS that can have a significant impact on the solution potential. Those are the validation of the selected ML algorithm (by trying and excluding other tested ML algorithms), the data format, the data preprocessing, and the data set size. [5, 6] The authors present characteristic components for MLS which measure characteristics of the ingested data. Since this translates into the overall prediction quality, these characteristic components are relevant for the purpose of this paper.

4.3 Characteristic components by BURKOV ET AL. and MÜLLER ET AL. [18, 19]

BURKOV ET AL. as well as MÜLLER ET AL. identify the importance of quantifying the performance of a functioning MLS. Both, metrics for the prediction quality as well as metrics on prediction and training speed are derived. The authors identify the performance metrics R^2 (for regressions), prediction accuracy (for classifications), training speed, and prediction speed. [18, 19] They state that there are different performance metrics that are characteristic of MLS. These metrics are of use for the goal of this paper as they give an indication of potential future performance of identified MLS patterns.

From the framework of SCHUH ET AL. as well as from the characteristic components of other authors a subset is chosen as part of the refined framework in the next chapter. This refined framework will be the foundation for the analysis and the results derived in Chapter VI.

5. Methodology

In this chapter the approach and the procedure used for the analyses of working MLS solutions in the following chapter is outlined. As described in the previous chapters, the goal of this paper is the simplification of implementing new MLS. It is hypothesized that similar problems might be efficiently tackled by similar solution approaches. Consequently, a search for patterns is necessary to prove or disprove this hypothesis. The underlying methodology will be explained in the following paragraphs and is split into four steps:

1. Determination of a suitable framework
2. Definition of a procedure for pattern search
3. Identification and selection of use cases
4. Literature analysis

The presented methodology is not considered without alternative, however, the approach to search for patterns had much success in the past, especially in the fields of design and action research [27]. Therefore, the above-mentioned steps are logically valid to produce a repeatable methodology in search of patterns in MLS.

For the development of a suitable framework, which is as complex as necessary and as effective as possible, it is crucial to leverage the most suitable literature and adapt it to the goal of this paper. As described in the previous chapters, SCHUH ET AL. have outlined a framework for MLS with many relevant characteristic components. However, this framework must be adapted, as it lacks important components, e.g., the data set size. Moreover, some parts of the framework are included for illustrational purposes, e.g., the influence of the development of AI. These parts will be removed in this work as they do not contribute to finding patterns. In the framework of SCHUH ET AL., the dimension *implementation procedure* e.g., consists of the sub-aspects programming language and programming library. However, these cannot be taken as characteristic components as the same solution can be implemented with different programming languages for example [28]. Two congruent approaches would have different manifestations regarding the characteristic programming language and therefore would lead to different paths in the framework. This would be a direct contradiction to the approach of this paper of finding patterns by having similar solutions resulting in similar paths in the framework. Therefore, these characteristic components will also be removed in this work as they do not contribute to finding patterns as well.

As explained previously, WUEST ET AL. and BURKOV ET AL. have identified additional relevant characteristic components of MLS (e.g. characteristic data components and performance metrics) [5, 18]. One of the main challenges in the CAP is the preparation of high-quality data [3, 5]. Since data quality is essential for MLS performance, it is useful to measure these manifestations in form of characteristic components. Of special interest are the two characteristic components data preprocessing and data set size, because they often determine a significant part of the effort/cost in real-world applications. The former describes – if any data preprocessing has been performed – which technique(s) have been used. The latter describes the data set size. Often, more data leads to better results of a MLS. However, such data generation for training purposes is mostly costly in industrial applications. Therefore, a good performing MLS with a smaller data set size is regarded as ideal. Including performance metrics to the bespoke framework is of high use because this way the success of a given implemented MLS can be quantified. It is not the goal of this work to derive patterns for average MLS, as the replication of average MLS will very likely result in another average MLS. Therefore, a distinction between the performance of an analyzed MLS is necessary. This is achieved by performance metrics. As one of the most widely used performance metrics, the coefficient of determination R^2 is a good characteristic component to measure performance of an implemented MLS [29].

In conclusion, the following six characteristic components of a successfully implemented MLS will be tied together in a framework. This framework will be used in the following to characterize MLS solutions. It serves to systematically compare various implemented MLS solutions.

Table 1: Bespoke framework dimensions

Dimensions & Results		
Characteristic Component	***Description***	***Source***
Machine learning strategy	Implementation approach	[7]
Machine learning goal	Goal of MLS	[7]
ML algorithm	Underlying mathematical algorithm	[7]
Dataset size	Data set size	[5]
Data preprocessing	Method of data pre-processing	[5]
R^2	Overall performance metric	[19]

The framework presented above is used for the analysis of all MLS covered in this research. In this paper three different use cases based on promising impact to the CAP are selected and their characteristic components are analyzed for patterns. The first use case to be analyzed is *quality prediction*. It is a promising field of research because modern CNC turning and milling machines are already equipped with many sensors. Thus, the required data basis is already available. However, the potential in this data is still largely untapped. [24] Connected to this is the second use case *wear prediction*. Using the above arguments, generated data is usually not used to predict tool wear. However, implemented MLS solutions can help reduce costs and machine downtimes and at the same time improve workpiece quality. [24] *Production planning* is explored as a third use case. Especially complex systems and production chains can profit from a more analytical approach. [3] From the perspective of the authors the three use cases described are both of significant importance to the CAP and potentially to be addressed with MLS. Additionally, there are a variety of different other use cases which are also suitable for selection, but these three were selected for initial analysis. Other use cases can be addressed in future research.

Following the definition of the three overarching use cases, a targeted search for potentially helpful literature is conducted in order to identify successfully implemented MLS. Firstly, the respective use case is combined with several keywords related to MLS. These keywords range from the simple addition ML to special algorithms. Thus, a list of possible publications for the respective use case is compiled. In a next step, a selection based on several criteria aiming to select publications of high quality is conducted. Criteria for the inclusion of a publication in the final selection are e.g., topic fit, extensive documentation, actual application of the ML methods, performance quality of the MLS used, validation of the MLS, and number of citations [30]. At this stage, no detailed content evaluation is performed but a rough selection of literature in a particular topic area is conducted in order to find as many successfully implemented MLS as possible. In a next step, each MLS of the respective literature foundation is examined in detail as well as characterized based on the framework presented. All examined and characterized publications can be found in the appendix. Finally, analyzing the characteristic components of all selected papers with respect to a particular use case, patterns can be identified. This is done by determining an “overlap percentage”, i.e., how many percent of other papers have the same characteristic component.

In this regard, it must be disclaimed that there might be more patterns in the selected use cases. In the following chapters, three patterns from different use case scenarios are presented. However, both the number of all possible use case scenarios and the potential set of all patterns within these scenarios exceed the selection presented in this paper.

6. Results

As described in the previous chapter, the search for patterns and the analysis of the underlying literature focusses on three use case areas: Quality prediction, tool wear prediction, and production planning. In the following paragraphs, the findings will be presented for each use case.

6.1 Quality prediction in metal cutting

Firstly, machine learning systems in the field of quality prediction of metal cutting in manufacturing are specifically investigated. [3]

Most of the publications deal with turning, milling, or drilling of steel or an alloy [22, 31–36]. The underlying objective of an MLS in this context is to predict the quality of the resulting part or the part surface based on process variables or parameters [31, 37]. In this context, process parameters refer to variables that remain constant throughout the entire manufacturing process, for example the feed rate in turning or the peripheral speed in milling [37]. Process variables are variables that are recorded during the manufacturing process and are typically not constant over time, for example the cutting force [38]. Both process variables and process parameters as well as their statistically characteristic values serve as input data set for the respective MLS. [3, 5, 21]

Since the goal is quality prediction, the quality must be numerically defined and measurable. In almost all publications, a surface roughness parameter was taken as the target value for this purpose, usually the average surface finish R_a or the averaged roughness depth R_z (variables named after standard material properties literature) [12, 39]. From several test series, it was thus possible to create training data sets from which the MLS generates a quality prediction model [18]. The test data set is then used to check how good the prediction model is on the basis of new data [19]. In the context of the publications examined, the following pattern can be identified (values for the coverage can be derived from the appendix):

Table 2: Pattern in quality prediction

Framework Analysis	Dimensions & Results		
	Framework Dimension	***Specification***	***Coverage***
(1)	ML learning strategy	Supervised Learning	100%
(2)	ML learning goal	Regression	94%
(3)	ML algorithm	Feedforward Neural Network	75%
(4)	Dataset size	≤ 34 for training purposes ≤ 15 for testing purposes	83%
(5)	Data preprocessing	No	75%
(6)	R^2	> 98%	73%

6.2 Tool wear prediction

Similar to the basic approach of quality prediction, the goal is the prediction of a property based on the process data. For this purpose, MLS are trained to classify tool wear or to regress it against a metric. [40]

The prediction of tool wear primarily serves to avoid quality declines due to excessively worn cutting edges or sudden tool failure [41]. Thus, tool wear prediction should not be considered as a direct value added, but more as an indirect value-added process. The potential of this use case is enormous, as seen in several publications [40, 42]. More specifically, several publications successfully attempted to make the prediction based on the raw data from multiple sensors alone [42–44]. This saves the time-consuming step of data preparation and in some cases feature engineering methods can be automated [40]. Both are crucial to leverage the potential of quality declines and avoid downtimes connected to this. In the context of the publications studied, the following pattern can be identified.

Table 3: Pattern in tool wear prediction

Framework Analysis	**Dimensions & Results**		
	Framework Dimension	***Specification***	***Coverage***
(1)	ML learning strategy	Supervised Learning	100%
(2)	ML learning goal	Regression	60%
(3)	ML algorithm	Long Short-Term Memory (LSTM)	60%
(4)	Dataset size	≤ 500 time series	83%
(5)	Data preprocessing	Yes, feature extraction	67%
(6)	R^2	≥ 81,3%	100%

6.3 Automated production planning

This use case differs from the two previously described in that the focus is not on a specific manufacturing process, but on the organization and interaction of different manufacturing processes [5]. Production planning generally deals with the question of how the production of several, usually different products can be carried out as optimally as possible [3]. One of the challenges of production planning is job-shop scheduling [45, 25].

The goal of job-shop scheduling is to identify the optimal allocation of production steps to machines. This allocation is carried out under technological boundary conditions (machine capacity, fixed production sequence), temporal boundary conditions (production times), logistic boundary conditions (local distribution of machines) as well as quantitative boundary conditions (product quantity to be produced). [3, 45] The abstract formulation of this problem is generally known as the job-shop scheduling problem (JSP) [45]. The JSP is a nondeterministic polynomial time-hard problem, which is particularly difficult to solve using traditional programming methods [5, 45, 46].

In addition to the mathematically derivable difficulty of solving the JSP, another challenge of machine scheduling is evident in practice: Responding to unforeseen events [5]. Bottlenecks in the supply chain, sudden machine breakdowns, or new high-priority orders – all of these events require rapid rescheduling of existing machine allocation schedules to ensure optimal allocation of intermediate products to resources. Consequently, the inclusion of unforeseen events would be a reasonable requirement for modern adaptive production planning [3].

In order to solve the machine occupancy scheduling problem while implementing the response to unforeseen events, the reinforcement learning strategy was used in all the publications studied [23, 47–56]. In interaction with a defined environment, the basic goal of reinforcement learning is the derivation of an optimal action strategy [20]. The action strategy is guided by a reward function, which is defined by the environment. The goal is to maximize the expected reward. [6, 18, 20] For automated production planning, the following pattern can be identified based on all publications examined:

Table 4: Pattern in production planning

Framework Analysis	Dimensions & Results		
	Framework Dimension	***Specification***	***Coverage***
(1)	ML learning strategy	Reinforcement Learning	100%
(2)	ML learning goal	n/a	n/a
(3)	ML algorithm	Q-learning algorithm	90.9%
(4)	Data set size	n/a	n/a
(5)	Data preprocessing	Yes, by construction of the data model	100%
(6)	Performance assessment (R^2 cannot be calculated)	Significantly better than heuristic methods	80%

In contrast to supervised and unsupervised ML methods, the ML learning goal for reinforcement learning is undefined according to SCHUH ET AL. [7] Furthermore, no data set size can be defined as this metric does not exist for reinforcement learning. For this particular ML learning strategy, the "data set" is inherent in the model which simulates the environment and the reward. For this reason, *metric (4)* of the table above is not applicable here.

From a practical point of view, previously identified patterns should enable users to develop new MLS more quickly. For example, for the first use case (quality prediction), the characteristic components (1) – (5) would be designing guidelines for the MLS. Especially the algorithm selection and the feature engineering might have a beneficial impact on the implementation efficiency. Characteristic component (6) will then give an expectation of the quality of the resulting MLS.

7. Discussion and Outlook

In summary, the goal of this paper was to identify successfully implemented MLS, to analyze them with respect to their implemented data analytics technologies, and to derive implementation heuristics for new implementation endeavors in the CAP. In Chapter I, it was outlined that the rising availability of sensor data and connectivity of machines drive the application of MLS that harbor significant untapped potential for cost reductions and production efficiencies. In Chapter II, it was found that the process of successfully implementing new ML solutions can be further improved. It was hypothesized that similar processes have similar underlying physical interrelationships, therefore similar solution approaches to similar problems should be possible. In Chapter III, existing literature was leveraged to build a framework for the analysis of MLS with respect to different use cases. Important characteristic components of MLS have been identified. Chapter IV clarified the methodology of this paper and in Chapter V, three patterns have been identified, which now can be utilized by practitioners when implementing MLS. Based on these results, further investigations need to be carried out. The identification of more patterns in other areas of the CAP is for example conceivable. This would help augmenting the speed of adoption and implementation of new MLS in the manufacturing industry.

Certain steps in the proposed methodology should be critically reflected. Firstly, the bespoke framework has been tailored to serve the purpose of this paper. It is also possible to derive a different, i.e., more detailed framework with more framework elements, and still conduct a search for patterns. Secondly, the amount of analyzed literature varies for each of the three analyzed use cases. In order to augment the validity of each pattern, the amount of analyzed literature for each use case could be further increased.

In summary, there is a need for further research in the use of MLS in the CAP. Possible directions for this are the areas of resource optimization, lead time prediction, fault diagnosis, process optimization, or machine condition monitoring, as all of these areas have a potentially high impact and are still dominated by traditional methods of optimization. Also, the identification of further patterns in the already presented application areas of MLS is conceivable.

Appendix

In the following three parts of the appendix, all the analyzed publications are presented. Furthermore, for each analyzed publication the manifestation of each framework dimension is outlined. The coverage of each framework dimension presented in Chapter VI is a direct derivation of the appended analysis.

A – Sources and analysis of quality prediction papers

Table 5: Literature – Quality prediction

Analyzed Paper	**Dimensions & Manifestations**					
	(1) ML Learning Strategy	***(2) ML learning goal***	***(3) ML algorithm***	***(4) Dataset size***	***(5) Data preprocessing***	***(6) R2***
ACAYABA ET AL. [31]	Supervised learning	Regression	Feedforward neural network (FNN)	273 training, 363 total	Cut-off of most extreme outliers (5%)	98,0%
BEATRICE ET AL. [32]	Supervised learning	Regression	FNN	24 training, 27 total	No	96,0%
CHANDRASEKARAN ET AL. [33]	Supervised learning	Regression	FNN	20 training, 25 total	No	94,2%
CODJO ET AL. [34]	Supervised learning	Classification	Support vector machines (SVM)	35 training, 14 testing	Feature selection & normalization	91,4%
DAS ET AL. [22]	Supervised learning	Regression	FNN	25 training, 31 total	Normalization	Not calculated
MIA ET AL. [35]	Supervised learning	Regression	FNN	34 training, 14 testing	No	99,7%
MIA ET AL. [36]	Supervised learning	Regression	FNN	27 training, 9 testing	No	97,5%
PIMENOV ET AL. [57]	Supervised learning	Regression	Random Forest (RF)	95 training, 105 total	No	Not calculated
QIN ET AL. [58]	Supervised learning	Regression	FNN	30 training, 10 testing	No	98,4%
SAHOO ET AL. [59]	Supervised learning	Regression	FNN	22 training, 5 testing	No	99,0%
SCHUH ET AL. [21]	Supervised learning	Regression	Extra Tree Regressor (XT)	120 training, 40 testing	Feature extraction & feature selection	91,7%
SENTHILKUMAR ET AL. [60]	Supervised learning	Regression	FNN	18 training	No	99,0%
TEBASSI ET AL. [61]	Supervised learning	Regression	FNN	10 training, 5 testing	No	98,9%
VENKATA ET AL. [43]	Supervised learning	Regression	FNN	54 training, 15 testing	Normalization	95,5%
VRABEL ET AL. [62]	Supervised learning	Regression	FNN	15 training, 14 testing, 14 validation	No	99,8%
ZHANG ET AL. [63]	Supervised learning	Regression	LS-SVM (least squares SVM)	15 training, 19 testing	No	94,4%
Total						
Manifest-ation	Supervised learning	Regression	FNN	≤ 34 training, ≤ 15 testing	No	> 98%
Coverage	100%	94%	75%	83%[a]	75%[a]	73%[b]

[a.] based on papers using the FNN algorithm

[b.] based on papers using the FNN algorithm and calculating R^2

B – Sources and analysis of tool wear prediction papers

Table 6: Literature – Tool wear prediction

Analyzed Paper	Dimensions & Manifestations					
	(1) ML Learning Strategy	***(2) ML learning goal***	***(3) ML algorithm***	***(4) Dataset size***	***(5) Data preprocessing***	***(6) R2***
AN ET AL. [42]	Supervised learning	Regression	Convolutional neural network (CNN) + Long short-term memory (LSTM)	500 x 0.5min samples	No (raw sensor data)	90,0%
CHEN ET AL. [64]	Supervised learning	Classification	CNN + bidirectional long short-term memory (BiLSTM) network with an attention mechanism (=CABLSTM)	1320 data samples with 3 physical properties	Feature extraction	97,0%
HASSAN ET AL. [65]	Supervised learning	Classification	LSTM	160 data samples with 5 signals each	Feature extraction	98,0%
KLANCNIK ET AL. [66]	Supervised learning	Classification	Artificial neural network (ANN)	18 samples with 108 features each	Feature extraction	92,6%
KUREK ET AL. [67]	Supervised learning	Classification	LSTM	242 Time series of 5 different physical quantities	Discrete Fourier transformation	81,3%
PROTEAU ET AL. [68]	Supervised learning	Regression	LSTM	16 samples with complete time series	No, but dataset is "already filtered"	90,0%
VENKATA ET AL. [43]	Supervised learning	Regression	ANN	54 training samples, 23 testing/validation samples	No	91,7%
WU ET AL. [40]	Supervised learning	Regression	Random Forest (RF)	285 training samples, 30 testing samples	Feature extraction	99,2%
WU ET AL. [69]	Supervised learning	Regression	RF	315 data samples with 7 signals each	Feature extraction	99,0%
ZHAO ET AL. [44]	Supervised learning	Regression	CNN + CABLSTM	6 signals, 315 data samples in total	No	Not calculated
Total						
Manifest-ation	Supervised learning	Regression	adapted LSTM	≤ 500 time series samples	Yes, feature extraction	≥ 81,3%
Coverage	100%	60%	60%	83%[c]	67%[c]	100%[d]

[c.] based on papers using the LSTM algorithm

[d.] based on papers using the LSTM algorithm and calculating R^2

C – Sources and analysis of production planning papers

Table 7: Literature – Production planning

Analyzed Paper	Dimensions & Manifestations					
	(1) ML Learning Strategy	***(2) ML learning goal***	***(3) ML algorithm***	***(4) Dataset size***	***(5) Data preprocessing***	***(6) Performance assessment***
KUHNLE ET AL. [47]	Reinforcement learning (RL)	not appli-cable (n/a)	Trust Region Policy Optimization (TRPO)-based RL-algorithm	not appli-cable (n/a)	Yes, through construction of data model	"promising results"
OU ET AL. [48]	Reinforcement learning	n/a	Q-learning algorithm (QLA)	n/a	Yes, through construction of data model	"significantly outperforms other policies"
PARK ET AL. [49]	Reinforcement learning	n/a	QLA	n/a	Yes, through construction of data model	"the proposed method outperformed the other baseline methods"
QU ET AL. [50]	Reinforcement learning	n/a	approximate QLA	n/a	Yes, through construction of data model	"we compare the result of this algorithm with heuristic methods and a multi-agent approach. It is verified that this method in general provides better results […] in complex settings"
QU ET AL. [51]	Reinforcement learning	n/a	multi-agent approximate QLA	n/a	Yes, through construction of data model	"successfully applied approach which can help to optimally assign workers and make up for a deficiency"
QU ET AL. [52]	Reinforcement learning	n/a	approximate QLA	n/a	Yes, through construction of data model	"The experimental results show that the learned dispatching rules are more cost efficient than most heuristic rules"
SHAHRABI ET AL. [53]	Reinforcement learning	n/a	Deep Q-learning algorithm (DQL) + variable neigh-bourhood search (VNS)	n/a	Yes, through construction of data model	"performance of the proposed method is significantly better than those of the common dispatching rules and GVNS"
SHIUE ET AL. [23]	Reinforcement learning	n/a	QLA	n/a	Yes, through construction of data model	"the proposed RL-based MDRs approach was significantly better than the SOM-based MDRs, SDR approaches, and other dispatching strategies."
WANG ET AL. [54]	Reinforcement learning	n/a	DQL + multi-agent reinforcement learning adaption (MARL)	n/a	Yes, through construction of data model	"outperforms traditional scheduling algorithms in terms of optimality of scheduling plans generated"
WASCHNECK ET AL. [55]	Reinforcement learning	n/a	DQL	n/a	Yes, through construction of data model	"Comparable to human with expert knowledge"
WASCHNECK ET AL. [56]	Reinforcement learning	n/a	DQL	n/a	Yes, through construction of data model	"The system automatically develops global optimal scheduling solutions without human intervention or any prior expert knowledge"
Total						
Manifest-ation	Reinforcement Learning	n/a	Variant of Q-learning algorithm	n/a	Yes, through construction of data model	Significantly better than heuristic methods
Coverage	100%	n/a	90,9%	n/a	100%	80%[e]

[e.] based on papers using the Q-learning algorithm

References

[1] Chryssolouris, G., Mavrikios, D., Papakostas, N., Mourtzis, D., Michalos, G., Georgoulias, K., 2009. Digital manufacturing: History, perspectives, and outlook. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 223 (5), 451–462.

[2] Heisel, U., Krug, R., 1989. Meßtastereinsatz in CNC-Maschinen reduziert Rüstzeitaufwand.

[3] Mayr, A., Kißkalt, D., Meiners, M., Lutz, B., Schäfer, F., Seidel, R., Selmaier, A., Fuchs, J., Metzner, M., Blank, A., Franke, J., 2019. Machine Learning in Production – Potentials, Challenges and Exemplary Applications. Procedia CIRP 86, 49–54.

[4] Parthasarathy, S., 2019. Difference between Traditional programming versus Machine Learning from a PM perspective. Product Coalition, April 22.

[5] Wuest, T., Weimer, D., Irgens, C., Thoben, K.-D., 2016. Machine learning in manufacturing: advantages, challenges, and applications. Production & Manufacturing Research 4 (1), 23–45.

[6] Géron, A., 2017. Hands-on machine learning with Scikit-Learn and TensorFlow: Concepts, tools, and techniques to build intelligent systems, First edition ed. O'Reilly Media, Beijing, Boston.

[7] Schuh, G., Scholz, P., 2019 - 2019. Development of a Framework for the Systematic Identification of AI Application Patterns in the Manufacturing Industry, in: 2019 Portland International Conference on Management of Engineering and Technology (PICMET). 2019 Portland International Conference on Management of Engineering and Technology (PICMET), Portland, OR, USA. 25.08.2019 - 29.08.2019. IEEE, pp. 1–8.

[8] Najafabadi, M.M., Villanustre, F., Khoshgoftaar, T.M., Seliya, N., Wald, R., Muharemagic, E., 2015. Deep learning applications and challenges in big data analytics. Journal of Big Data 2 (1).

[9] McKinsey Global Institute, 2017. Artificial Intelligence - The next digital frontier? McKinsey Global Institute, 1–80.

[10] Capgemini Research Institute, 2019. Scaling AI in Automotive Industry, 1–36.

[11] Rohrback, T., 2017. Führungskräfte bremsen digitale Transformation aus. https://www.scope-online.de/smart-industry/industrie-4-0--fuehrungskraefte-bremsen-digitale-transformation-aus.htm. Accessed 17 June 2020.

[12] Schlageter, L., Rateitschak-Plüss, E.M., Schwarz, J.P., 1996. Root surface smoothness or roughness following open debridement. An in vivo study. Journal of Clinical Periodontology 23 (5), 460–464.

[13] Ho, Y.C., Pepyne, D.L., 2002. Simple Explanation of the No-Free-Lunch Theorem and Its Implications. Journal of Optimization Theory and Applications 115 (3), 549–570.

[14] McKinsey Global Institute, 2018. Visualizing the uses and potential impact of AI and other analytics | McKinsey. https://www.mckinsey.com/featured-insights/artificial-intelligence/visualizing-the-uses-and-potential-impact-of-ai-and-other-analytics. Accessed 16 June 2020.

[15] Klocke, F., König, W., 2008. Fertigungsverfahren 1: Drehen, Fräsen, Bohren, 8 Aufl. ed. Springer-Verlag, Berlin, Heidelberg.

[16] Surmann, T., 2006. Geometrisch-physikalische Simulation der Prozessdynamik für das fünfachsige Fräsen von Freiformflächen. Zugl.: Dortmund, Univ., Diss., 2005. Vulkan-Verl., Essen.

[17] Hurwitz, J., Kirsch, D., 2018. Machine Learning for Dummies, IBM Limited Edition ed. John Wiley & Sons, Hoboken, NJ.

[18] Burkov, A., 2019. The hundred-page machine learning book.

[19] Müller, A.C., Guido, S., 2017. Introduction to machine learning with Python: A guide for data scientists, First edition ed. O'Reilly Media, Sebastopol, CA.

[20] Raschka, S., Mirjalili, V., 2018. Python machine learning: Machine learning and deep learning with Python, scikit-learn, and TensorFlow, Second edition ed. Packt Publishing, Birmingham, Mumbai.

[21] Schuh, G., Scholz, P., Schorr, S., Harman, D., Möller, M., Heib, J., Bähre, D., 11232019. Prediction of Workpiece Quality: An Application of Machine Learning in Manufacturing Industry, in: 6th International Conference on Computer Science, Engineering and Information Technology (CSEIT-2019). 6th International Conference on Computer Science, Engineering and Information Technology. 23/11/2019. Aircc Publishing Corporation, pp. 189–202.

[22] Das, B., Roy, S., Rai, R.N., Saha, S.C., 2015. Studies on Effect of Cutting Parameters on Surface Roughness of Al-Cu-TiC MMCs: An Artificial Neural Network Approach. Procedia Computer Science 45, 745–752.

[23] Shiue, Y.-R., Lee, K.-C., Su, C.-T., 2018. Real-time scheduling for a smart factory using a reinforcement learning approach. Computers & Industrial Engineering 125, 604–614.

[24] McKinsey Digital, 2017. Smartening up with artificial intelligence, 1–52.

[25] Khan, A., Turowski, K., 2016. A Survey of Current Challenges in Manufacturing Industry and Preparation for Industry 4.0, in: Abraham, A., Kovalev, S., Tarassov, V., Snášel, V. (Eds.), Proceedings of the First International Scientific Conference "Intelligent Information Technologies for Industry" (IITI'16), vol. 450. Springer International Publishing, Cham, pp. 15–26.

[26] Gaur, M., 2014. Performance Evaluation of Machine Learning Techniques using Software Cost Drivers. IJCA 89 (16), 10–18.

[27] Dixon, D., 2012. Analysis Tool or Research Methodology: Is There an Epistemology for Patterns?, in: Berry, D.M. (Ed.), Understanding digital humanities. Palgrave Macmillan, Houndmills, New York, NY, pp. 191–209.

[28] Geek, 2017. Top 5 best Programming Languages for Artificial Intelligence field - GeeksforGeeks. https://www.geeksforgeeks.org/top-5-best-programming-languages-for-artificial-intelligence-field/. Accessed 25 June 2020.

[29] Seif, G., 2018. The 5 Basic Statistics Concepts Data Scientists Need to Know. Towards Data Science, October 22.

[30] V. Knight, L., A. Steinbach, T., 2008. Selecting an Appropriate Publication Outlet: A Comprehensive Model of Journal Selection Criteria for Researchers in a Broad Range of Academic Disciplines. IJDS 3, 59–79.

[31] Acayaba, G.M.A., Escalona, P.M.d., 2015. Prediction of surface roughness in low speed turning of AISI316 austenitic stainless steel. CIRP Journal of Manufacturing Science and Technology 11, 62–67.

[32] Beatrice, B.A., Kirubakaran, E., Thangaiah, P.R.J., Wins, K.L.D., 2014. Surface Roughness Prediction using Artificial Neural Network in Hard Turning of AISI H13 Steel with Minimal Cutting Fluid Application. Procedia Engineering 97, 205–211.

[33] Chandrasekaran, M., Devarasiddappa, D., 2014. Artificial neural network modeling for surface roughness prediction in cylindrical grinding of Al-SiCp metal matrix composites and ANOVA analysis. Adv produc engineer manag 9 (2), 59–70.

[34] Codjo, L., Jaafar, M., 2018. Milling diagnosis using machine learning techniques toward Industry 4.0. DX@Safeprocess 2018.

[35] Mia, M., Dhar, N.R., 2016. Prediction of surface roughness in hard turning under high pressure coolant using Artificial Neural Network. Measurement 92, 464–474.

[36] Mia, M., Razi, M.H., Ahmad, I., Mostafa, R., Rahman, S.M.S., Ahmed, D.H., Dey, P.R., Dhar, N.R., 2017. Effect of time-controlled MQL pulsing on surface roughness in hard turning by statistical analysis and artificial neural network. Int J Adv Manuf Technol 91 (9-12), 3211–3223.

[37] Campanelli, S.L., Ludovico, A.D., Bonserio, C., Cavalluzzi, P., Cinquepalmi, M., 2007. Experimental analysis of the laser milling process parameters. Journal of Materials Processing Technology 191 (1-3), 220–223.

[38] Diei, E.N., Dornfeld, D.A., 1987. Acoustic Emission from the Face Milling Process—the Effects of Process Variables. J. Eng. Ind 109 (2), 92–99.

[39] Goodhand, M.N., Walton, K., Blunt, L., Lung, H.W., Miller, R.J., Marsden, R., 2016. The Limitations of Using "Ra" to Describe Surface Roughness. J. Turbomach 138 (10).

[40] Wu, D., Jennings, C., Terpenny, J., Gao, R.X., Kumara, S., 2017. A Comparative Study on Machine Learning Algorithms for Smart Manufacturing: Tool Wear Prediction Using Random Forests. Journal of Manufacturing Science and Engineering 139 (7).

[41] Scheffer, C., Kratz, H., Heyns, P.S., Klocke, F., 2003. Development of a tool wear-monitoring system for hard turning. International Journal of Machine Tools and Manufacture 43 (10), 973–985.

[42] An, Q., Tao, Z., Xu, X., El Mansori, M., Chen, M., 2020. A data-driven model for milling tool remaining useful life prediction with convolutional and stacked LSTM network. Measurement 154, 107461.

[43] Venkata Rao, K., Murthy, B., Mohan Rao, N., 2014. Prediction of cutting tool wear, surface roughness and vibration of work piece in boring of AISI 316 steel with artificial neural network. Measurement 51, 63–70.

[44] Zhao, R., Yan, R., Wang, J., Mao, K., 2017. Learning to Monitor Machine Health with Convolutional Bi-Directional LSTM Networks. Sensors (Basel, Switzerland) 17 (2).

[45] Applegate, D., Cook, W., 1991. A Computational Study of the Job-Shop Scheduling Problem. ORSA Journal on Computing 3 (2), 149–156.

[46] Gaspers, S., 2010. Exponential Time Algorithms: Structures, Measures, and Bounds. VDM Verlag Dr. Müller, Saarbrücken.

[47] Kuhnle, A., Schäfer, L., Stricker, N., Lanza, G., 2019. Design, Implementation and Evaluation of Reinforcement Learning for an Adaptive Order Dispatching in Job Shop Manufacturing Systems. Procedia CIRP 81, 234–239.

[48] Ou, X., Chang, Q., Chakraborty, N., 2019. Simulation study on reward function of reinforcement learning in gantry work cell scheduling. Journal of Manufacturing Systems 50, 1–8.

[49] Park, I.-B., Huh, J., Kim, J., Park, J., 2020. A Reinforcement Learning Approach to Robust Scheduling of Semiconductor Manufacturing Facilities. IEEE Trans. Automat. Sci. Eng., 1–12.

[50] Qu, S., 2016. 21th IEEE Conference on Emerging Technologies and Factory Automation (ETFA): September 6 - 9, 2016, Berlin. IEEE, Piscataway, NJ.

[51] Qu, S., Chu, T., 2015. A Centralized Reinforcement Learning Approach for Proactive Scheduling in Manufacturing. IEEE Trans. Automat. Sci. Eng. 2015.

[52] Qu, S., Wang, J., Govil, S., Leckie, J.O., 2016. Optimized Adaptive Scheduling of a Manufacturing Process System with Multi-skill Workforce and Multiple Machine Types: An Ontology-based, Multi-agent Reinforcement Learning Approach. Procedia CIRP 57, 55–60.

[53] Shahrabi, J., Adibi, M.A., Mahootchi, M., 2017. A reinforcement learning approach to parameter estimation in dynamic job shop scheduling. Computers & Industrial Engineering 110, 75–82.

[54] Wang, Y., Liu, H., Zheng, W., Xia, Y., Li, Y., Chen, P., Guo, K., Xie, H., 2019. Multi-Objective Workflow Scheduling With Deep-Q-Network-Based Multi-Agent Reinforcement Learning. IEEE Access 7, 39974–39982.

[55] Waschneck, B., Reichstaller, A., 2018. 2018 29th Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC): April 30, 2018-May 3, 2018. IEEE, Piscataway, NJ.

[56] Waschneck, B., Reichstaller, A., Belzner, L., Altenmüller, T., Bauernhansl, T., Knapp, A., Kyek, A., 2018. Optimization of global production scheduling with deep reinforcement learning. Procedia CIRP 72, 1264–1269.

[57] Pimenov, D.Y., Bustillo, A., Mikolajczyk, T., 2018. Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth. J Intell Manuf 29 (5), 1045–1061.

[58] Qin, X., Wang, B., Wang, G., Li, H., Jiang, Y., Zhang, X., 2014. Delamination analysis of the helical milling of carbon fiber-reinforced plastics by using the artificial neural network model. J Mech Sci Technol 28 (2), 713–719.

[59] Sahoo, A.K., Rout, A.K., Das, D.K., 2015. Response surface and artificial neural network prediction model and optimization for surface roughness in machining. 10.5267/j.ijiec 6 (2), 229–240.

[60] Senthilkumar, N., Tamizharasan, T., 2015. Flank wear and surface roughness prediction in hard turning via artificial neural network and multiple regressions. Australian Journal of Mechanical Engineering 13 (1), 31–45.

[61] Tebassi, H., Yallese, M.A., Meddour, I., Girardin, F., Mabrouki, T., 2017. On the Modeling of Surface Roughness and Cutting Force when Turning of Inconel 718 Using Artificial Neural Network and Response Surface Methodology: Accuracy and Benefit. Period. Polytech. Mech. Eng. 61 (1), 1–11.

[62] Vrabel, M., Maňková, I., Beňo, J., 2016. Monitoring and Control of Manufacturing Process to Assist the Surface Workpiece Quality When Drilling. Procedia CIRP 41, 735–739.

[63] Zhang, N., Shetty, D., 2016. An effective LS-SVM-based approach for surface roughness prediction in machined surfaces. Neurocomputing 198, 35–39.

[64] Chen, Xie, Yuan, Huang, Li, 2019. Research on a Real-Time Monitoring Method for the Wear State of a Tool Based on a Convolutional Bidirectional LSTM Model. Symmetry 11 (10), 1233.

[65] Hassan, M., Sadek, A., Attia, M.H., 2019. A Generalized Multisensor Real-Time Tool Condition–Monitoring Approach Using Deep Recurrent Neural Network. Smart Sustain. Manuf. Syst. 3 (2), 20190020.

[66] Klancnik, S., Ficko, M., Balic, J., Pahole, I., 2015. Computer Vision-Based Approach to End Mill Tool Monitoring. Int. j. simul. model. 14 (4), 571–583.

[67] Kurek, J., Swiderski, B., Jegorowa, A., Kruk, M., Osowski, S., 2017. Deep learning in assessment of drill condition on the basis of images of drilled holes, in: Eighth International Conference on Graphic and Image Processing (ICGIP 2016). Eighth International Conference on Graphic and Image Processing, Tokyo, Japan. Saturday 29 October 2016. SPIE, 102251V.

[68] Proteau, A., Tahan, A., Thomas, M., 2019. Specific cutting energy: a physical measurement for representing tool wear. Int J Adv Manuf Technol 103 (1-4), 101–110.

[69] Wu, D., Jennings, C., Terpenny, J., Kumara, S., 2016 - 2016. Cloud-based machine learning for predictive analytics: Tool wear prediction in milling, in: 2016 IEEE International Conference on Big Data (Big Data).

2016 IEEE International Conference on Big Data (Big Data), Washington DC,USA. 05.12.2016 - 08.12.2016. IEEE, pp. 2062–2069.

Biography

Prof. Dr.-Ing. Dipl.-Wirt. Ing. Günther Schuh holds the chair for Production Systematics at RWTH Aachen University. Furthermore, he is director of the FIR e. V., member of the board of directors of the WZL of the RWTH Aachen University and the Fraunhofer Institute for Production Technology (IPT).

Paul Scholz works as a research assistant and project leader at the Fraunhofer-Institute for Production Technology. He completed Master’s degrees both at RWTH Aachen University and Tsinghua University Beijing.

Johannes Portik is a student currently enrolled at RWTH Aachen University as well as Harvard University.