Design Patterns for Monitoring and Prediction Machine Learning Systems: Systematic Literature Review and Cluster Analysis

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Abstract: Although machine learning methods for industrial maintenance systems have already been well described in recent years, their practical implementation is only slowly taking place. One of the reasons is a lack of comparable analyses of machine learning systems. To address this gap, we first conducted a systematic literature review (2012–2021) of 104 monitoring and prediction systems. Second, we extracted 5 design patterns (i.e., high-level construction manuals) based on a k-means cluster analysis. Our results show that monitoring and prediction systems mainly differ in their choice of operations. However, they usually share similar learning strategies (i.e., supervised learning) and tasks (i.e., classification, regression). With our work, we aim to help researchers and practitioners to understand common characteristics, contexts, and trends.

1 INTRODUCTION

The manufacturing industry produces an ever increasing data amount due to the digitalization of machines (e.g., cyber-physical systems) (Tang et al., 2014). The generated data is particularly valuable for applications that are able to use it in machine learning systems (MLS), enabling diverse possibilities, such as monitoring and prediction applications (Monostori et al., 2016). Since the costs of maintaining machines is a major part of the total costs of manufacturing systems (Mobley, 2002), the importance of monitoring and prediction systems, e.g., condition monitoring (CM) or predictive maintenance (PM) applications, increased in recent years (Motaghare et al., 2018; Serin et al., 2020). However, their practical implementation in actual manufacturing companies is only slowly taking place, e.g., due to a missing understanding of relevant technological layers (Schuh et al., 2020). Usually, MLS lack comparable investigations of their technological structure. So, despite the extensive research regarding maintenance systems, we are missing a comprehensive systematization of MLS which is oriented towards a comparable tool to extract design patterns representing their technological structure. Precisely, we define a design pattern as the systematization of the most frequently occurring characteristics of a specific software system, i.e., a high-level construction manual as a decision aid for system design and development, consisting of principal MLS-related properties. In this context, we argue that similar problems offer similar solution patterns. Thus, these patterns may provide a high transferability to facilitate the transfer of theoretical described MLS into practice. Moreover, design patterns can provide a highly valuable basis for the engineering process of MLS software for both researchers and practitioners (Schuh et al., 2020).

Overall, **our goal is to classify and discuss the technological structure of monitoring and prediction MLS**. To achieve this goals, we first conduct a systematic literature review (SLR) of 104 papers (2012–2021). Second, the results of the SLR are further analyzed by applying a k-means clustering algorithm. In detail, we contribute the following:

- An analysis of the current state-of-the-art of monitoring and prediction MLS (SLR).
- An identification and discussion of monitoring and prediction design patterns (clustering).
- An open-access repository to ensure a replicability of our study.[1]

With our results, we aim to provide an understanding and uniform decision aid for the design and implementation of MLS in the manufacturing industry.

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2 BACKGROUND

Next, we provide information regarding *MLS* and *monitoring and prediction systems*.

2.1 Machine Learning Systems

Machine learning (ML) refers to the artificial acquisition of information based on experiences (e.g., sensor data), which can be applied to new data to start learning processes (Patil et al., 2017) that reduce time, costs, or improve product and process quality (Wang et al., 2018). When ML is implemented in a holistic system to address such value added, the resulting system is called MLS (Schuh et al., 2020). Overall, MLS are mostly categorized in terms of their learning strategies, tasks, and operations (Dogan and Birant, 2021). *Learning strategies* are related to the way information is generated, including 3 major categories: supervised learning, unsupervised learning, and reinforcement learning (Wuest et al., 2016). *Tasks* refer to how systems receive feedback according to the learning strategies, e.g., classification (Schuh and Scholz, 2019). *Operations* involve models or methods used to fulfill tasks, e.g., support vector machines (SVM) or artificial neural networks (ANN) (Schuh et al., 2020).

2.2 Monitoring and Prediction Systems

Monitoring and prediction mainly refer to the term *maintenance*, which is considered as part of operation phases in the product and machine life cycle (IEC 60300-3-3:2017, 2017). Precisely, *Monitoring* refers to identifying the current condition state of a machine or process. So, it is focused on the derivation of symptoms (e.g., failure) based on input data, e.g., generated by sensors (VDI/VDE 2651 Part 1:2017-05, 2017). *Prediction* (also called prognosis) deals with the derivation of future machine or tool conditions based on the previous and current conditions. Predictive techniques estimate the remaining useful life (RUL) based on retrieved data to improve operating time and to schedule maintenance tasks (ISO 13372:2012, E/F). Usually, the selection of suitable monitoring and prediction systems is made in relation to the failure and wear behavior of a system. This selection depends on the use case, such as tool wear monitoring (TWM), i.e., determining the actual condition state, or tool wear prediction (TWP), i.e., estimating the RUL and (actual) condition states in relation to following machining cycles. However, MLS provide diverse operations to address diverse types of systems or analytics, making the appropriate selection of strategies highly challenging (Qiao et al., 2020).

3 METHODS

To achieve our research goal, we employed an SLR (Kitchenham et al., 2015) to collect data and analyzed it by applying a k-means clustering algorithm to extract common design patterns (cf. Figure 1).

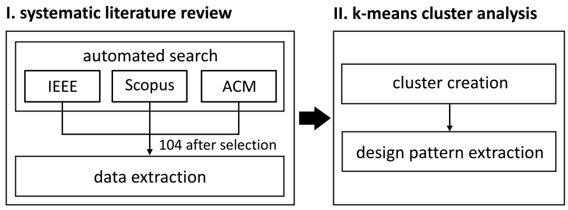

Figure 1: Methodological overview consisting of 2 steps.

3.1 Systematic Literature Review

In the following sections, the methodological steps of the SLR are described.

3.1.1 Study Design

Search String. To identify suitable papers, the following search string consisting of relevant terms in the context of MLS, manufacturing, and maintenance was applied to SCOPUS, IEEE XPLORE, and the ACM GUIDE TO COMPUTING LITERATURE.

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("machine learning" OR "deep learning"
OR "artificial intelligence" OR "neural
network") AND "manufacturing" AND ("machine
tool" OR "cutting" OR "machining" OR
"turning" OR "milling" OR "drilling" OR
"CNC") AND ("condition monitoring" OR
"predictive maintenance" OR "tool wear
prediction")
```

Selection Criteria. We selected only papers that have been published in 2012–2021 at a conference or in a journal and deal with manufacturing-related MLS approaches focusing on CM, PM, or TWP. As we did not perform a detailed quality assessment of all papers, a certain quality was ensured by defining a minimum of 3 pages of only peer-reviewed papers.

Extraction Criteria. To extract data, we relied on an extended version of the framework by Schuh and Scholz (2019) as it provides a well-founded basis for a uniform classification of MLS approaches:

- **Manufacturing Processes**, i.e., actual manufacturing operations performed by a machine, e.g., milling (Sevic and Keller, 2019).
- **Machines**, i.e., hardware performing certain manufacturing processes, e.g., a CNC machine (Krishna and Kannadaguli, 2020).
- **Use Cases**, i.e., technological tasks of the application, e.g., monitoring of health state in water pumping (Griffiths, 2020).

- **Technology Value Add**, i.e., economic incentives to use ML-driven technology, e.g., improvement of quality, time, or costs (Wang et al., 2018).
- **Implementation Procedures**, i.e., tools for developing the MLS, e.g., programming languages such as Python (Lutz et al., 2019).
- **Working Areas**, i.e., ML-related activities or application fields, e.g., CM (Davies, 2012).
- **Learning Strategies**, i.e., the strategy used by MLS to learn from data, e.g., supervised learning (Goodfellow et al., 2016).
- **Tasks**, i.e., main workflows used to recognize certain patterns in data, e.g., classification or clustering (Schuh et al., 2019).
- **Operations**, i.e., representation forms and characteristics of the tasks applied for analysis purposes, e.g., decision trees or ANN (Schuh et al., 2019).
- **Data Base**, i.e., data used to learn, e.g., vibration data (Espinoza Sepúlveda and Sinha, 2021).

3.1.2 Study Conduct

The first and second authors conducted an automated search on December 01, 2022, retrieving 246 publications (231 after duplication removal). Next, the publications' titles and abstracts were analyzed to identify the approaches relevant for our study (111 papers). To find missing related articles, we performed backward snowballing with an unrestricted number of iterations (117 papers). After reading the full-texts, we selected 104 papers. These papers are not explicitly listed in our paper, but can be accessed via the open access repository including their analysis.[1]

3.2 Cluster Analysis

An unsupervised k-means algorithm was implemented (scikit-learn, Python 3.9) to recognize patterns in the collected data (Kanungo et al., 2002). The clustering method consists of the following 5 steps:

1. Text values (i.e., extracted MLS properties) are converted into numerical values, including the correction of assignments. We mitigated the threat of affecting the external validity by excluding the technology value add and implementation procedures. Both properties contained too little information or too much space for interpretation.
2. Cluster seeds were initialized randomly according to a predefined number of expected clusters. In this context, the elbow method was used which suggested a number of 5 clusters as appropriate.
3. The Euclidean distance between each point and seed was calculated by our method, meaning the smallest distance became part of the given seed.
4. The seeds were placed in the centroids of the generated clusters to become their representatives.
5. The numerical values are converted to their text values, including the correction of assignments.

4 RESULTS

Next, the SLR and clustering results are described (organized according to monitoring and prediction).

4.1 Literature Review Results

This section presents the results of the SLR. For reasons of simplicity, each publication that is concerned with CM, PM, and TWP is assigned to its predominant concern.

4.1.1 Monitoring Systems

We selected 67 monitoring MLS publications. Note that we do not address working areas since we only focus on CM.

Manufacturing Processes. The most mentioned manufacturing process is milling (32). Others include cutting (10), turning (8), drilling (4), grinding (3), and sawing (2), which are typically concerned with a specific use case, e.g., gun drilling. Besides, we found processes that were unique and thus could not be classified adequately, e.g., processes for bearings (2).

Machines. The majority of the papers refers to CNC machines (49). The remaining publications focus on diverse (parts of) machines, e.g., lathes (4).

Use Cases. We divide the use cases into 2 categories: monitoring approaches regarding the condition of machines, machine parts or their components (62), or monitoring approaches focusing on the workpiece (5). Most papers refer to CM of machines, machine parts, or components, including TWM or tool CM. The second category was mentioned by less papers, however, also including 2 TWM approaches.

Technology Value Add. We identified 5 major incentives for monitoring MLS, including improving manufacturing quality (51), product quality (32), productivity (38) and life time (12), and reducing waste/consumption (16) to reduce costs (50).

Learning Strategies. The majority of the monitoring systems is based on supervised learning (54). A small number of publications refers to unsupervised learning (8) or a combination of supervised and unsupervised learning methods (5).

Tasks. 38 publications are based on classification. Moreover, there exist 2 approaches using a combination of dimension reduction with classification al-

gorithms. 20 papers mention regression as their task. Furthermore, there exist combinations of regression and dimension reduction (2) or clustering algorithms (1). Only few papers refer solely to clustering (3).
Operations. Most approaches are based on ANN (23), including traditional ANN (15). In addition, 14 papers are based on convolutional NN (CNN), including besides the traditional CNN specific forms, Bayesian CNN. Moreover, we found approaches using SVM (10) or recurrent NN (RNN) (6), e.g., recurrent long-short term memory network. The remaining papers present various ML operations, such as decision trees (4), autoencoders (3), ensemble algorithms (2), c-means (2), k-star (1), or deep belief networks (1). We also identified several mixed operations occurring only once, e.g., ANN and cluster analysis.
Data Base. The dominant signals used as a single data base are vibration (36), force (21), audio (19), images (6), current (9), and power (6). The combinations of signals are commonly based on force or vibration and include other signals, such as audio, temperature, or power. Moreover, we found out that the most applied combination is force, vibration, and audio signals (9).
Implementation Procedures. The most preferred programming language is MATLAB (21). Moreover, in 11 publications the usage of Python is described, usually in terms of libraries, such as Tensorflow. Others include G (3), Visual Basic (1), Java (1), Excel (1), and both Python and MATLAB (2). 27 papers did not mention a certain implementation procedure.

4.1.2 Prediction Systems

We selected 37 prediction MLS publications. Note that we intentionally considered both PM and TWP.

Manufacturing Processes. The most common process is milling (22). Others include cutting (5), turning (3), or machining (2). Among the general process categories, there are several use case-specific manufacturing processes, e.g., laser melting.
Machines. The most common machines are CNC machines (28). Other machines mentioned are linear axes (2), lathes (2), steckel mills (1), melting machines (1), and wafer-handling robotics (1). Two papers that did not focus on a specific machine (2).
Use Cases. The use cases are mainly in the context of TWP (31). Prediction systems are typically combined with monitoring processes, e.g., bearing CM and TWP of the machine tools. Other papers relied on more specific prediction use cases, such as degradation state prediction.
Technology Value Add. The major incentives are improving manufacturing quality (30), product quality (16), productivity (25) and tool life (10), and reducing waste (9) to reduce costs (31).
Working Areas. We extracted 2 working areas: traditional PM (14) and TWP (23). Both areas are primarily concerned with predicting future conditions for maintaining purposes rather than monitoring.
Learning Strategies. Most papers are based on supervised learning (27). A small number of papers refer to unsupervised learning (5). Others rely on a combination of supervised and unsupervised learning methods (4). 1 approach is based on semi-supervised learning.
Tasks. The most common task is regression (19). In addition, combinations of regression with other tasks were found, e.g., classification (1) or dimension reduction (2). Classification is mentioned in 9 cases. We also found 2 combinations of dimension reduction and classification. Moreover, there are also clustering (3) and dimension reduction approaches (1).
Operations. ANN are implemented the most (8), including traditional ANN and deep NN. Other operations mentioned in the papers are CNN (6), ensemble algorithms (6), decision trees (5), RNN (4), cluster analyses (3), SVM (3), and Bayesian approaches (3). These general categories often include use case-specific operations, e.g., multi-scale convolutional gated recurrent unit networks.
Data Base. The most frequently signals used are vibration (22), force (17), and audio (14). Combinations of signals are more common than single signals, mostly based on at least force or vibration.
Implementation Procedures. The majority did not mention an implementation procedure (27). Concrete programming languages are rarely mentioned, e.g., Python (4), MATLAB (3), or G (1).

4.2 Cluster Analysis Results

In this section, we present the clustering results based on the k-means method applied to the SLR data. Overall, we identified 5 clusters, where each cluster represents a design pattern (cf. Table 1).

4.2.1 Monitoring Design Patterns

We identified 3 relevant clusters for monitoring MLS.

Monitoring Design Pattern 1. This pattern (22% of all monitoring approaches) comprises supervised learning, classification, and ANN/CNN, i.e., 2 operations. Vibration signals (67%) are used the most as data base for the certain learning processes. This design pattern refers mainly to cutting processes by CNC machines. Precisely, it is focused on CM applications for machines, parts, or individual compo-

Table 1: Monitoring and prediction design patterns based on the framework of Schuh and Scholz (2019).

	Monitoring			Prediction	
Technological layer	**Design pattern 1**	**Design pattern 2**	**Design pattern 3**	**Design pattern 1**	**Design pattern 2**
Manufacturing processes	cutting	milling	milling	milling	milling
Machines	CNC	CNC	CNC	CNC	CNC
Use cases	TWM/TWP	TWM/TWP	TWM/TWP	TWM/TWP	TWM/TWP
Working areas	CM	CM	CM	TWP	PM
Learning strategies	supervised learning	supervised learning	supervised learning	supervised learning	supervised learning
Tasks	classification	classification	regression	regression	classification
Operations	CNN/ANN	ANN/CNN/SVM	ANN	CNN/ANN/ensemble	ANN/clustering/RNN
Data base	vibration	acoustic/vibration	vibration/force	vibration/force/acoustic	vibration

nents. For example, the pattern is actually implemented by Alegeh et al. (2019).

Monitoring Design Pattern 2. The most applied pattern (40% of all monitoring approaches) is based on a combination of supervised learning, classification, and ANN/CNN/SVM, i.e., diverse operations. Vibration and acoustic signal (both 37%) are mentioned the most. Force is only described in 26% of the papers. The characteristics regarding machines and process focus on milling for CNC machines. The use case is usually TWM or TWP. For instance, this pattern is followed by Kotsiopoulos et al. (2021).

Monitoring Design Pattern 3. This pattern (37% of all monitoring systems) relies on supervised learning, regression, and ANN, e.g., fulfilled by Javed et al. (2012). Data bases are vibration (64%) and force (56%). Moreover, it refers mainly to CNC-based milling where the use case is mostly TWM or TWP.

4.2.2 Prediction Design Patterns

We found 2 prediction clusters, i.e., 2 design patterns.

Prediction Design Pattern 1. Regarding the first design pattern (59% of all prediction approaches), the combination of supervised learning, regression, and CNN/ANN/ensemble algorithms, i.e., diverse operation, is most common. Interestingly, design pattern 1 consists exclusively of TWP approaches, which are a dominant decisive criteria. The data base of these TWP approaches typically consists of force (59%), vibration (59%), and acoustic signals (41%). Similar to 2 monitoring patterns, methods for milling with CNC machines are often proposed. For instance, this design pattern is followed by Li et al. (2021).

Prediction Design Pattern 2. This pattern (41% of all prediction approaches) relies on supervised learning, classification, and ANN/cluster analysis/RNN, i.e., diverse operations. The data base used is usually based on vibration signals (64%). Similar to pattern 1, this pattern focuses on milling for CNC machines. Interestingly, all but 1 paper deals with PM, which indicates that the working area is decisive here. For example, this pattern is addressed by Luo et al. (2018).

5 DISCUSSION

Next, the extracted design patterns are compared to each other, additional findings are presented and threats to validity are discussed.

5.1 Design Pattern Comparison

Monitoring Design Patterns. First, the monitoring design patterns are mainly characterized by their MLS tasks. While the first and second pattern deal with classification, the third pattern focuses on regression tasks. Second, in all patterns TWM and TWP are the most mentioned use cases. Here, the paper count increases with cluster number, i.e., design pattern 1 has the lowest and design pattern 3 the highest proportion, i.e., classification MLS are applicable in more diverse applications. Third, the manufacturing processes correspond to the machines. So, in pattern 2 and 3 milling is most common. In contrast, the first pattern consists primarily of cutting and barely milling processes. Fourth, while in design pattern 1 mainly vibration is used, design pattern 2 is quite balanced based on acoustic, vibration, or other data like force and current. Design pattern 3 is focused on vibration, force, and acoustic.

Prediction Design Patterns. First, the major difference are the working areas (i.e., TWP and PM). We argue that most other differences in the technology layers are caused by this fact. Second, although TWM/TWP is the most applied use case in both patterns, the proportion in the first design pattern is significantly higher corresponding to the working area. While TWM/TWP is the only use case in design pattern 1, the second pattern shows more diverse use cases, e.g., machine health monitoring. Third, a similar situation exists regarding the machine and the corresponding process (i.e., CNC and milling). Fourth, while the first pattern deals in general with regression tasks, classification is dominant in the second pattern. Thus, supervised learning is the main strategy for both. However, the second pattern consists of more unsupervised learning applications, possibly due to the fact that PM requires much data from various data sources. These are not only limited to information from machines or processes but also from the maintenance management system. In consequence, MLS in PM applications comprise upstream dimension reduction or clustering methods to handle the complexity of high dimensional huge amounts of data. Fifth, design pattern 1 consists mainly of vibration, force, and acoustic signals related to the working area and use case TWM/TWP. Design pattern 2 is more balanced, except the dominance of vibration, i.e., showing many other information, such as power or temperature.

Monitoring & Prediction Design Patterns. The design patterns seem quite similar, but there is a significant number of differences. The ratio between monitoring and prediction is about 2:1, possibly due to the fact that prediction is located on a higher complexity level than monitoring. This assumption is emphasized by the prediction approaches which address more unsupervised learning tasks. In addition, prediction MLS mainly use regression in contrast to monitoring which are usually based on classification. We argue that regression is more suitable to prediction systems because it deals with continuous target values in contrast to classification with discreet target variables. As a result, monitoring MLS deploy more ANN, CNN, and SVM while prediction MLS are significantly more balanced with a higher number of RNN, ensemble methods, and variations of DT which are very powerful, e.g., on time series data.

5.2 Additional Findings

Data Base. Interestingly, the design patterns are mostly based on a similar data base: vibration or force, sometimes also acoustic signals. The main reason for this particularity is the use of open data sets, e.g., the PHM challenge data set or the NASA milling data set. We highlight that such data sets are the basis for uniform and comparable evaluations of MLS regardless of their working area. By considering the same evaluation metrics, ideally based on evaluation criteria or practice-oriented MLS requirements, assessments could increase in value. So, the qualitative assessment of the operations could be supported by a benchmark with quantitative evaluation criteria, e.g., accuracy or efficiency.

Learning Strategies. The extracted learning strategies seem quite similar, i.e., the MLS are usually based on supervised learning. We assume that supervised learning is often implemented because it is currently one of the most common learning strategies and is well suited due to its associated tasks, i.e., classification in the context of monitoring MLS and regression in the context of prediction MLS. Furthermore, it is conceivable that the implementation of more complex forms of learning such as reinforcement learning is still too challenging or too critical referring to data security or privacy (e.g., data manipulation).

Machines. The majority of the MLS approaches is based on CNC machines. This fact indicates the widespread use of CNC machines in small and medium-sized manufacturing companies, mainly due to their flexibility. We argue that this finding could also be related to the use of the open data sets. However, there is a number of machine tools that cannot be addressed by our design patterns in detail, even though we support the trend towards CNC machines.

Technology Value Add. The technology value add is quite similar in most of the cases, i.e., improving quality and productivity, as well as reducing costs. These incentives are closely related to the widespread triangle of production (Wang et al., 2018). However, we note that more than 3 properties would also be feasible in the manufacturing domain, e.g., by adding flexibility (Erlach, 2013).

5.3 Threats to Validity

There are several threats that could impair the validity of our study.

Systematic Literature Review. We could not find out whether all authors share the same understanding of certain terms, e.g., monitoring systems with actual predictive capabilities. However, this fact exemplifies the convergence of these technologies to benefit from their specific strengths in different contexts. In addition, there was a lack of completeness in depth of content and consistency. Interestingly, more than half of the authors did not mention a concrete learning strategy, leading to assignments by ourselves (e.g., tasks as indicator for learning strategies). Nevertheless, misclassifications cannot be excluded. Although we are aware of the fact that an even higher number of papers might have gone beyond the thematic scope of the paper, we know that the lower the number of papers, the higher the impact of misinterpretations.

Clustering. There is no guarantee for an objective validity of the generated clusters, e.g., k-means is sensitive to outliers that could mitigate our validity. So, it is important to validate our design patterns based on the clusters and further investigate the exact nature and role of the approaches that do not entirely fit in one of the design patterns.

Although the described issues could threaten our findings, we aimed to mitigate them, e.g., we relied only on peer-reviewed publications of 3 relevant databases. Moreover, in several previous studies, it was already demonstrated that the selected framework is appropriate and valuable for the uniform classification of MLS, e.g., Schuh et al. (2020). Note that we mitigated the threat of possibly affecting the external validity of the identified design patterns by excluding the technological layers that do not provide enough or reliable information, namely technology value add and the implementation procedures. Overall, we argue that our study is highly valuable, reproducible, and provides detailed insights into monitoring and prediction MLS research.

6 RELATED WORK

We are aware of related work in our subject areas. However, none of these publications provides a comparable overview of the technological structure from a technology management perspective. In contrast, our study is based on a successfully evaluated framework that has been developed by practitioners and researchers to identify design patterns. In the following we present a selection of the closest related work.

Monitoring Systems. Serin et al. (2020) employed a study to summarize CM systems using deep learning and described opportunities of CM in Industry 4.0 environments. Mohanraj et al. (2020) presented a literature review focusing on monitoring methods for tool CM in the milling process which have been described in manufacturing-related literature. Soother and Daudpoto (2019) as well as Choudhary et al. (2019) reviewed CM techniques in an engineering context (induction motors). However, Choudhary et al. (2019) focused more on the fault diagnosis process and diagnostic schemes.

Prediction Systems. Zonta et al. (2020) presented a literature review of PM applications in Industry 4.0 environments focusing on existing methods, standards, and applications. Carvalho et al. (2019) published a literature review of ML methods focusing on their performance, challenges, and opportunities in the context of PM. Theissler et al. (2021) surveyed PM approaches in the automotive industry from an application and ML perspective. Moreover, Çınar et al. (2020) reviewed smart manufacturing PM applications by focusing on ML-related criteria, such as data acquisition and data classification.

7 CONCLUSION

We presented a comprehensive overview of monitoring and prediction MLS in the manufacturing industry, i.e., performing a classification of 104 papers and extracting 5 design patterns.

We conclude that research on monitoring and prediction MLS is quite diverse. This trend is highlighted by the growing capabilities of MLS, their operations, and tasks in recent year, especially in the field of NN. We emphasize the dependence of MLS operations and tasks on use cases, the resulting systems' variability, as well as the high impact of data sets on the comparability of MLS. We strongly recommend continuing research, e.g., analyzing further MLS working areas and manufacturing-related diagnosis applications.

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