Computers & Industrial Engineering 149 (2020) 106773

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Survey

Machine learning applications in production lines: A systematic literature review

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ARTICLE INFO

Keywords:
Machine learning
Production lines
Data analytics
Data mining
Systematic literature review

ABSTRACT

A production line is a set of sequential operations established in a factory where materials are put through a refining process to produce an end-product that is suitable for further usage. Monitoring production lines is essential to ensure that the targeted quality of the production process and the products are achieved. With the increased digitalization, lots of data can now be generated in the overall production line process. In parallel, the generated data sets are used by machine learning techniques for analytics of the production line to improve quality control, evaluate risks, and save cost. This paper aims to identify, assess, and synthesize the reported studies related to the application of machine learning in production lines, to provide a systematic overview of the current state-of-the-art and, as such, paving the way for further research. To this end, we have performed a Systematic Literature Review (SLR) in which we retrieved 271 papers, of which 39 primary studies were selected for a detailed analysis. This SLR presents and categorizes the production line problems addressed by machine learning, identifies the targeted industrial domains, discusses which machine learning algorithms have been used, and explains the adopted independent and dependent variables of the models. The study highlights the open problems that need to be solved and provides the identified research directions.

1. Introduction

The new industrial paradigms such as Manufacturing 2.0, Industry 4.0, Smart Factory, and Internet of Things (IoT) are becoming increasingly popular (Riel, Kreiner, Macher, & Messnarz, 2017) as these concepts are making the manufacturing production process more flexible, more adaptable to personalization, and more traceable (Luque, Peralta, de las Heras, & Córdoba, 2017). The application of IoT technology has significantly increased during the last decades, and the manufacturing sector experienced a substantial growth rate within the last decade. With the rapid development of Industry 4.0 and IoT technologies, more and more real-time on-site data is collected from production lines. Nowadays, it is possible to use data-driven methods to provide solutions for different production line problems.

Production lines often have to deal with a diverse set of concerns. Different production lines consist of different problems that require numerous data and approaches. As a response to these problems, modeling is prevalently adopted to optimize the operation of the production lines and adopt mathematical and/or computational approaches to optimize the process often in a cost-effective and cost-efficient manner. Hereby, for example, fast and accurate simulations of the operation of a production process are performed, which provides insight in and helps to assist the management of the production line. However, developing and programming models is time-consuming, expensive, and requires high domain expertise. For small manufacturers, it may not be possible at all to afford this cost for their production lines. On the other hand, even large-scale manufacturers have to cope with the recurring complexity and lack of efficiency in constructing models for various production processes.

One of the key concerns in problems in production lines is fault detection in production lines, for which it is cumbersome to develop general solutions, and thus a certain customized production line may not be applicable to others (Ngo & Schmitt, 2016). In contrast to program models, it has been indicated that data-driven quality management can handle mass production systems more effectively. In particular, machine learning techniques have been shown very effective in analyzing complex systems and solving problems in the domain of manufacturing.

Although machine learning has been proven to be an effective tool to analyze complex relationships and problems, it is still not clear which problems in production lines can be effectively solved with the help of

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https://doi.org/10.1016/j.cie.2020.106773
Received 5 April 2020; Received in revised form 22 July 2020; Accepted 16 August 2020
Available online 19 August 2020
0360-8352/

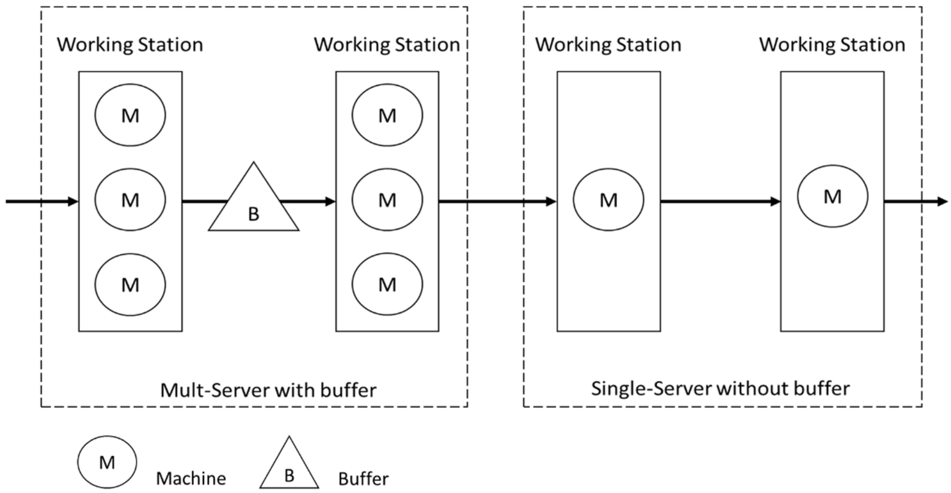

Fig. 1. Production line concept model with multi-server and single server working stations.

machine learning approaches. Also, the production line is a very broad concept, and different industries have numerous production line setups, and as such, they have to cope with diverse problems during production. For instance, some production lines can generate a huge number of data, and in such a case, machine learning techniques can provide remarkable solutions; however, a similar solution may not be effectively applied in other production lines due to the limited data.

This review paper is different than the traditional literature review papers (a.k.a., survey papers) because we systematically search in electronic databases, identify the relevant papers, extract the required data, and synthesize them to respond to our research questions. This type of review is called Systematic Literature Review (SLR) that reviews primary studies published on a particular topic. In an SLR study, researchers do not summarize the content of various papers; instead, the literature is systematically grouped and categorized to answer the identified specific research questions.

To the best of our knowledge, this is the first SLR study on the use of machine learning techniques for production lines, and as such, this research is timely and makes explicit the valuable information for practitioners and researchers. We adopted the SLR protocol of Kitchenham et al. (2009) and followed the ideas discussed in the paper of Tummers, Kassahun, and Tekinerdogan (2019). We retrieved 271 papers from scientific databases, and 39 papers (Can & Heavey, 2016; Lihao & Yanni, 2018; Wang, Liu, Gong, & Zhang, 2018; Wang, Cao, Huang, & Zhang, 2017; Wang, Gao, & Yan, 2017; Golkarnarenji et al., 2018, 2019; Milo, Roan, & Harris, 2015; Vincent, Duhamel, Ren, & Tchernev, 2015; Liu, Jin, Wu, & Herz, 2020; Mulrennan et al., 2018; Fritzsche, Richter, & Putz, 2017; Tsai & Lee, 2017; Schnell et al., 2019; Oestersötebier, Traphöner, Reinhart, Wessels, & Trächtler, 2016; Pattarakavin & Chongstitvatana, 2016; Luo & Wang, 2018; Xiao et al., 2018; Wang & Yang, 2017; Wu, Zhou, Cao, Shi, & Liu, 2018; Moldovan, Cioara, Anghel, & Salomie, 2017; Susto, Pampuri, Schirru, Beghi, & De Nicolao, 2015; Li, Wang, & Li, 2016; Zhang, Xu, & Wood, 2016; Melhem, Ananou, Djeziri, Ouladsine, & Pinaton, 2015; Besseris, 2015; Liu, Zhou, Tsung, & Zhang, 2019; Wang, Liu, Ge, Ling, & Liu, 2015; Feng, Gao, & Liu, 2018; Corne, Nath, El Mansori, & Kurfess, 2017; Principi, Rossetti, Squartini, & Piazza, 2019; Karagiorgou et al., 2019; Mangal & Kumar, 2016; Pani & Mohanta, 2016; Duhamel, Vincent, Tchernev, & Ren, 2015; Munirathinam & Ramadoss, 2016; Kim, Han, & Lee, 2016; Wen, Li, Gao, & Zhang, 2017; Razavi-Far, Farajzadeh-Zanjani, Zare, Saif, & Zarei, 2017) were selected after the selection criteria, and the quality assessment is applied. This review paper presents the synthesis of these papers published recently. This paper systematically reviews the state-of-the-art in this domain and paves the way for further research on the application of machine learning in production lines.

The following sections are organized as follows: Section 2 presents the background and related work. Section 3 describes the methodology. Section 4 discusses the results, and Section 5 explains the discussion. Finally, Section 6 presents the conclusions.

2. Background and related work

In this section, we first explain the notion of production lines, their characteristics, and metrics to evaluate the quality of production lines in Section 2.1. Further, we describe machine learning types and machine learning tasks in Section 2.2.

2.1. Production lines

Production lines are used to automate the production of a broad set of products, and hence it has been used in many industrial domains. Various different definitions of the notion of production lines can be identified. In this study, we refer to the definition presented in the study of Bierbooms (2012), which defines a production line as a manufacturing or assembly process where materials are sequentially processed to make a product at the end. With the help of this manufacturing process, raw materials go through a series of working stations and end up with a final product. For an assembly production line, components from other production lines are assembled to build a complex product. Assembly production lines largely exist in car manufacturing and complex equipment manufacturing.

Production lines can be classified into *job-shop*, *batch*, *repetitive*, *continuous*, and *mass production* categories. For more accurate classification, the specific production line characteristics need to be defined. According to Bierbooms (2012), four production line characteristics can be defined to classify the production lines, namely production volume, working station arrangement, buffer, and process type. These characteristics are explained as follows:

- **Production volume** (low/high): In a low volume production line, the cycle time is relatively long as a result of high flexibility and diversity. Lots of human intervention and limited automation exist during the production process. Generally, the job-shop production line has low production volume, as in the case of precision equipment manufacturing and luxury car production. On the other hand, production lines like food processing and paper manufacturing do not have many requirements for customization and, therefore, can have a high throughput. In the high-volume production, the machinery setup is less flexible, and the production lines run at a very high speed without many workers.

- **Working station arrangement** (single server or multi-server): A working station consists of one or multiple machines performing one task. The single server stands for one machine in a working station while multi-server stands for multiple machines working in parallel in a working station. The single server setup is simple and easy to operate, but the availability is highly uncertain. The multi-server setup alleviates the consequence of individual machine failure, but it also increases the system complexity.
- **Buffers** (with buffer or without buffer): The buffer can indicate the space between two working stations. It can convey a belt or a pipeline. The buffer has two functions in a production line. First, it transports products from one station to the next station. Second, it provides buffer storage to handle the cycle time variation between two connected working stations. A working station does not stop immediately when the upstream working station breaks down if there is a buffer in-between.
- **Process type** (discrete or continuous): In a discrete production line, the cycle time of a working station varies. A machine must stop if the downstream buffer is full, and the machine starts to work again after space is available in the downstream buffer. This is called Booking-After-Services (BAS). The continuous production line has a non-stopped production flow. The cycle time of the machine is adjusted to make sure that there is no congestion in the upstream and downstream buffer. One effective way to distinguish between continuous and discrete process types is to look at the product order. For the continuous production line, the product is an order in volume while the order is per unit for a discrete production line.

Basically, a production line has three components, which are the *working station, machine,* and *buffer*, as shown in Fig. 1. One working station can contain one or more machines performing the same task. Buffer transports products between two working stations and provides buffer storage. Some working stations do not have a buffer. For modeling, two adjacent working stations, along with the buffer, are treated as a subsystem. Equilibrium functions are derived from each subsystem, and the whole production line can be modeled in an iterative way (Kleinrock et al., 1976).

Several metrics are used to assess the quality of production lines. Among these, the *Overall Equipment Effectiveness (OEE)* is widely used as a method to evaluate the effectiveness of the equipment, and it consists of three indexes: *Availability*, *Performance*, and *Quality* (Dal, Tugwell, & Greatbanks, 2000) as shown in equation (1). *Availability* refers to the percentage of machinery downtime (Eq. (2)); *Performance* describes the percentage of the maximum operational speed (Eq. (3)); *Quality* refers to the percentage of a good product (Eq. (4)). The level of these three indexes links to other machinery's operational characteristics such as energy consumption, waste generation, and yield. For instance, the yield of a production line is determined by the machine running speed, percentage of machine uptime as well as the final product pass rate. Similarly, a production line with low performance and low product pass rate tend to have low energy efficiency and high waste generation. In summary, Availability, Performance, and Quality are three fundamental indexes describing the performance of a production line.

$$OEE = Availability \times Performance = \frac{no.Good\ \ count \times Theoretical\ \ Cycle\ \ Time}{no.Produced} \tag{1}$$

$$Availability = \frac{Actual\ \ Operating\ \ Time}{Planned\ \ Operating\ \ Time} \tag{2}$$

$$Performance = \frac{no.Produced \times Theoretical\ \ Cycle\ \ Time}{Actual\ \ Operating\ \ Time} \tag{3}$$

$$Quality = \frac{no.Produced - no.Fail}{no.Produced} \tag{4}$$

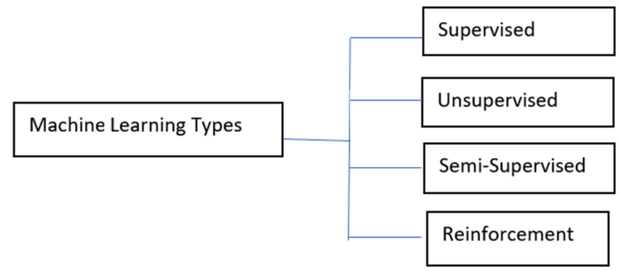

Fig. 2. Overview of machine learning types.

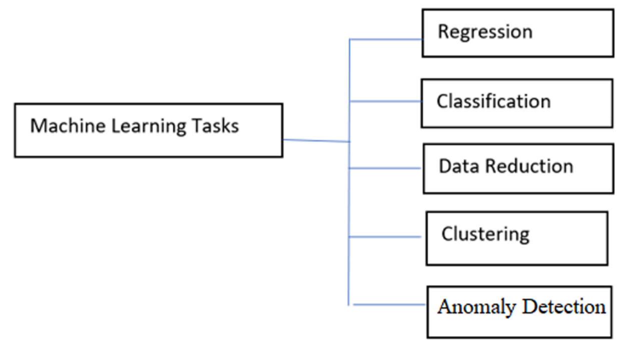

Fig. 3. Overview of machine learning tasks.

2.2. Machine learning

Machine learning enables computer programs to perform complex tasks such as prediction, diagnosis, planning, and recognition by learning from historical data. Data and algorithms are crucial for the performance of machine learning models. High-quality data and large data sizes can mostly increase the accuracy of machine learning models. It is also essential to apply proper algorithms to solve different problems, including different kinds of datasets. An overview of the machine learning types and the tasks which can be addressed by machine learning algorithms are presented in Fig. 2 and Fig. 3, respectively.

Machine learning types are explained as follows:

- **Supervised Learning**: The computer program derives a function between the input(s) and the output(s) from a set of labeled training data. Human intervention plays an important role in supervised learning. People not only label the output for the training set but also select the features, algorithms, and even control parameters of algorithms based on several assumptions of algorithms. Supervised learning is generally used in fields where the human has certain knowledge and some expertise for a model. However, the supervised learning approach requires more data processing for feature selection and expects parameter optimization for a better configuration of the algorithm.
- **Unsupervised Learning**: Unlike supervised learning, this machine learning type does not require labeled data. Unsupervised learning is usually used when relationships among input variables are not known. Instead of providing an output value like in the case of supervised learning, unsupervised learning provides the pattern of input variables and mostly presents different clusters built based on the input data.
- **Semi-supervised Learning**: In supervised learning, labeled data is used to train the model, and it makes the model more robust and accurate; however, the data labeling process is expensive. In several cases, only a small portion of the data is labeled while the majority of the data points are unlabeled. Semi-supervised learning algorithms can train a model with both labeled and unlabeled data, which can

provide better accuracy compared to the supervised model that uses very limited labeled data.

- **Reinforcement Learning**: In reinforcement learning, agents observe the environment, perform some actions, and get some rewards (negative/positive) based on the selected action, and then the model is updated accordingly. The reinforcement learning type uses a feedback mechanism to reward positive action and punish the negative action. This approach is, for example, used in self-driving cars and online games such as backgammon.

Machine learning techniques are applied in numerous areas to solve different kinds of tasks. Five common tasks are explained as follows:

- **Regression**: Regression, which is also known as value estimation, maps the input features to a numerical continuous variable. Machine learning algorithms are used to optimize the coefficients of each independent variable to achieve a minimum error in the prediction. The output variable can be either an integer or a floating-point number.
- **Classification**: Classification maps input features to one of the discrete output variables. The output variable represents a class for the underlying problem. For binary classification, the output variable can only be one or zero. For multi-class classification, the output variable can consist of several classes.
- **Clustering**: Clustering divides data points into relevant groups. This grouping is based on the similarity pattern between data points. Similar points are grouped together and provide valuable information to data scientists.
- **Data Reduction**: The data reduction tasks can reduce the number of features, and also, it is possible to remove some of the rows (i.e., data points) due to the noisy data instances or repetitive data points. For building models faster, some of the features that are highly correlated or that are not very relevant might be removed from the dataset. This task is mainly used as an auxiliary method for other machine learning tasks such as regression and classification.
- **Anomaly Detection**: Anomaly detection task is primarily handled with unsupervised learning methods. Similar to the clustering, anomaly detection algorithms group the samples. The outliers are determined in the dataset with the help of anomaly detection algorithms.

3. Methodology

In this section, we describe the research questions, search process, study selection criteria, quality assessment approach, data collection, and data synthesis steps. The SLR guideline and the protocol of Kitchenham et al. (2009) have been strictly followed in this research. After the research questions have been identified, the search strategy has been defined, and relevant papers have been retrieved from scientific databases. Study selection criteria have been applied to the retrieved papers, and a subset of these papers have been determined for quality assessment. After a careful examination of each paper based on the quality assessment questions, the final subset of papers, including 39 papers, have been identified. These papers have been carefully read by researchers, and research questions have been answered.

3.1. Research Questions (RQs)

We defined the following research questions for this SLR study. We selected these RQs because the responses to these questions would allow us to perform primary studies and develop new models for some of the identified open problems in this study.

1. Which industry domains apply machine learning for production lines?
   a. What type of production lines are addressed?
   b. What type of target processes are used?
2. Which OEE index of a production line can be predicted with machine learning approaches?
3. Which production line problems are addressed with machine learning?
4. What kind of machine learning approaches are applied?
   a. What kind of machine learning types are applied?
   b. What kind of machine learning tasks are addressed?
   c. What kind of machine learning algorithms are used?
5. What are the dependent and independent variables used in these models?

Table 1
Exclusion criteria.

ID	Criterion
1.	The full text is not accessible
2.	The paper is not written in English
3.	The article is a review or is not primary research
4.	The content is not falling within the concept of OEE
5.	The paper is not explicitly discussing problems of the continuous production line
6.	The paper does not explain in detail how machine learning has been applied

Table 2
Quality evaluation questions. Yes scores 2; Partial scores 1; No scores 0.

ID.	Questions	Yes (2)	Partial (1)	No (0)
Q1	Are the aims of the study clearly stated?			
Q2	Are the scope and context of the study clearly defined?			
Q3	Is the proposed solution clearly explained and validated by an empirical study?			
Q4	Are the variables used in the study likely to be valid and reliable?			
Q5	Is the research process documented adequately?			
Q6	Are all study questions answered?			
Q7	Are the negative findings presented?			
Q8	Are the main findings stated clearly in terms of creditability, validity, and reliability?			

3.2. Search process

The source of the search was online digital databases, which include IEEE Xplore, Science Direct, ACM Digital Library, and Wiley Online Library. Due to the fast development of IoT, cloud computing, and Artificial Intelligence technologies, the major industrialized countries initiated their industrial upgrading plan in the next ten years, such as the smart industry and Industry 4.0 (Qian, 2017). To this end, production lines have been recently upgraded, and therefore, this SLR searched for articles published between 2014 and 2019. During this SLR study, relevant papers are also extracted from the reference of selected papers and from papers citing these identified papers (a.k.a., backward/forward snowballing). Different combinations of keywords were used to refine the scope of the search. Finally, the following query is determined:

"production line" AND ("machine learning" OR "deep learning" OR "neural network")

The results of this search are shown in Table 3.

3.3. Selection criteria

In order to obtain a comprehensive overview of this field, many articles were retrieved from electronic databases. After reading the abstract and the introduction sections of each paper, the searched results were filtered based on the exclusion criteria shown in Table 1. The result of the application of selection criteria is presented in Table 3.

Table 3
Process of paper selection.

Source	After query search	After applying the selection criteria	After quality assessment
IEEE Xplore	36	18	16
Science Direct	111	23	18
ACM	60	1	1
Wiley	58	3	2
Manual Search	6	2	2

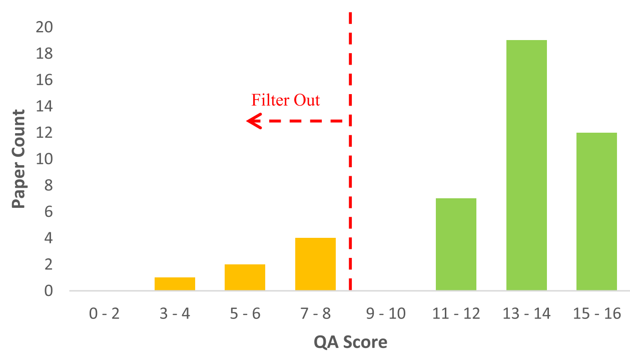

Fig. 4. Quality assessment result.

3.4. Quality assessment

The selected papers were then scored according to the quality evaluation method described by Kitchenham and Charters (2007). The quality of a paper was assessed by a list of questions listed in Table 2. In order to further refine the search, papers with a score lower than eight were excluded from the list. The result of the quality assessment process is shown in Fig. 4. The number of selected papers after the quality assessment is also presented in Table 3. After the selection criteria are applied, and a quality assessment is performed. We reached 39 papers that are listed in Section 7.2 - Primary Studies.

3.5. Data collection

A data extraction form shown in Appendix A was used to collect the required data. Because not all relevant data are clearly presented in some papers, the following assumptions have been made:

- **Buffer**: Buffer generally exists in production lines. However, most of the research papers do not use the buffer in the analysis. Therefore, the field 'buffer' is 'Yes' only when the article specifically mentioned buffer elements in the analysis.
- **Working Station Characteristics**: Similar to the buffer, the field is 'Yes' only if the paper specifically mentioned a single server or multi-server.
- **Production Volume**: Low-volume production line tends to have high automation, high customization, and produces complex products. The high-volume production line tends to have low automation, fixed setup, and produces simple products. For instance, the automobile production line has high complexity and low volume, while the food processing line is normally low complexity and high volume (Synnes & Welo, 2016). However, the high-volume production line can have a low-volume production process and verse vice. If the paper discusses a particular process of the production line, the production volume characteristic is determined by that process.
- **Process Type**: Whether a production line is continuous or discrete is usually not mentioned in research papers. Therefore, the process type is determined by the process work, industry domain, and cycle time. For example, a production line with a short cycle time producing liquid products is considered as a continuous production line.
- **Industry Domain**: The industry domain classification refers to the source from the United States Department of Labor (Labor, 2019).

3.6. Data synthesis

The data synthesis aggregates the collected data to answer the research questions. One or multiple data extracted from the data extraction form can be used to respond to one research question. We answer the research questions in both a qualitative and quantitative way. For qualitative questions, we summarised the collected data from previous papers. For instance, the industry domain is categorized according to the definition of the United States Department of Labor (2019). For quantitative questions, we retrieve the values based on the literature and count the number of papers related to that target topic. For example, machine learning algorithms related question is answered based on the number of papers used this type of algorithms.

4. Results

In this section, we present our responses to the research questions of this research. Each response is also supported by a figure that reflects the current status.

4.1. RQ1. Which industry domains apply machine learning for production lines?

The classification of the industry domain refers to the classification of the United States Department of Labor (Labor, 2019). As depicted in

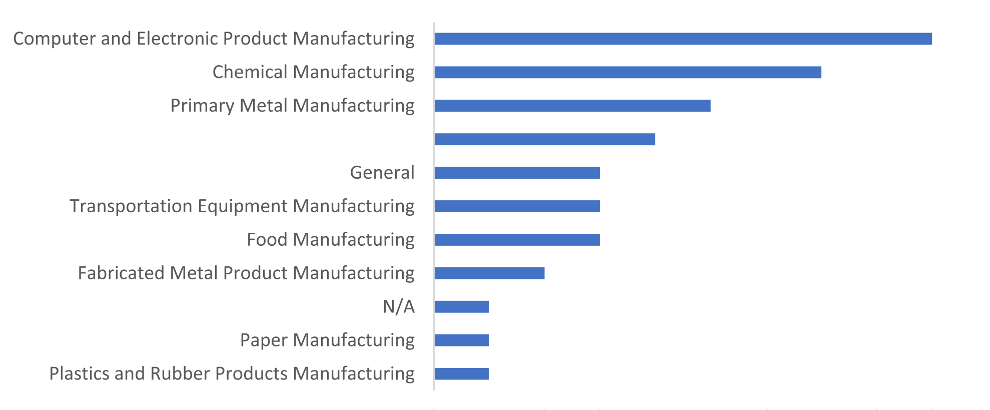

Fig. 5. Distribution of machine learning applications with respect to industry domains.

Table 4
Distribution of production line types.

Buffer		Process Type		Production Volume		Working Station	
Yes	10%	**Discrete**	49%	**High**	59%	**Single-Server**	72%
No	92%	**Continuous**	46%	**Low**	36%	**Multi-Server**	23%

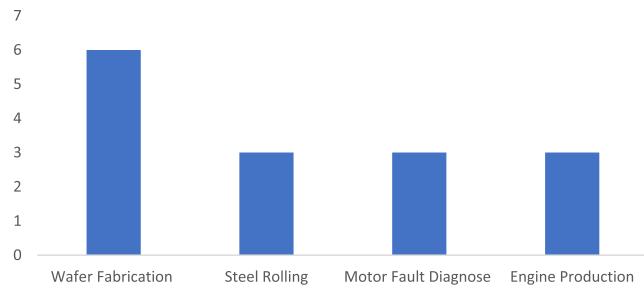

Fig. 6. Top four production processes applied machine learning.

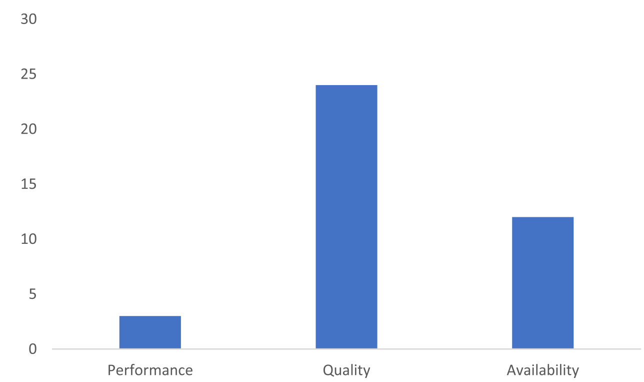

Fig. 7. Distribution of papers in terms of the OEE index.

Fig. 5, the computer and electronics manufacturing accounts for nearly a quarter of the studies. Chemical manufacturing and metal industry are at the second and third ranks with a percentage of 18% and 13%. The General category refers to the motor fault diagnosis, which can be applied to all kinds of production lines, and the Not Applicable (N/A) category indicates that no industry domain information is accessed from the paper.

4.1.1. RQ1.a What type of production lines are addressed?

Table 4 presents the production line type distribution based on four characteristics. It shows that most production lines do not have a buffer, or the buffer was not specifically specified in the study. Similarly, more than 70% of studies focused on the single server working station, which means that the use of parallel working machines was not explained in these studies. Another finding is that the number of discrete production lines is similar to the number of continuous production lines.

4.1.2. RQ1.b What type of target processes are used?

There are more than twenty production processes across multiple industry domains. The top-four processes shown in Fig. 6 have significantly more occurrence than the other processes. Especially, the wafer fabrication process is discussed in six papers, while the rest appeared three times in 39 papers. The motor fault diagnosis application is also explained in three papers, but they are not production processes, and, as such, they are not included.

Table 5
Descriptions of the reported production line (PL) problems.

PL Problem	Description
Quality optimization	Decrease the product failure rate at the end of the production line. Optimize key performance index of the final product to meet customer needs.
Fault diagnosis	Prognostic diagnose of production line failure event. Identify the malfunction part of the production line. Predict the unnormal behaviors of machines and equipment.
Product failure detection	Detects the products that do not meet the standard of production. The failure product is not counted in the final production volume. A high failure rate leads to low production volume.
Scheduling optimization	Logistic management of the production line, which can maximize the throughput of the production line. Buffer control and product routing management.
Waste reduction	Optimize material utilization rate during the production process. Reduce failure product rate to avoid waste of material.
Yield improvement	Increase the throughput of the production line by better scheduling management and lower failure product rate.
Preventive maintenance	Increase the availability of the production line by preventing the breakdown of equipment in advance. Predict the risk of malfunction of the production line and arrange proactive maintenance.

4.2. RQ2. Which OEE index of a production line can be predicted with machine learning approaches?

All three OEE indexes are studied in the selected papers. However, quality-related machine learning application is the dominant area, as shown in Fig. 7. 24 out of 39 papers discuss how machine learning can be used to improve the output quality of a production line. For instance, the application of machine learning can be used to reduce the product failure rate for production lines. It was observed that very few studies focused on the performance index of OEE. Three papers targeting performance index are all related to the production line cycle time improvement.

4.3. RQ3. Which production line problems are addressed with machine learning?

Most papers investigate solutions for quality-related problems, including quality optimization, product failure detection, waste reduction, and yield improvement, as shown in Table 5 and in Table 6. Quality optimization and product failure detection are the two most investigated problems, which appeared 14 and 8 times, respectively. Regression is the main machine learning task applied for quality optimization problems, while classification and anomaly detection are major tasks for product failure detection. Availability related problems are investigated in 13 papers, of which fault diagnosis is the most discussed topic. Binary classification is the major machine learning task for the fault diagnosis problems. There are only two papers that applied machine learning in the preventive maintenance domain.

4.4. RQ4. What kind of machine learning approaches are applied?

In this subsection, we provide the answers to three sub research questions that are related to the machine learning approaches. The distribution of machine learning types, machine learning tasks, and machine learning algorithms are presented.

4.4.1. RQ4.a What kind of machine learning types are applied?

According to Fig. 8, supervised learning is the dominant machine learning type applied for production lines. Some studies used both supervised and unsupervised learning methods. Therefore, the sum of the two categories is greater than 100%.

Table 6
Production line problems and reported OEE category, ML task, and adopted dependent variable.

PL Problem	OEE Category	ML Task	Dependent Variable (Most frequent)	Count
Quality optimization	Quality/Performance	Regression	Continuous measurements	14
Fault diagnosis	Availability	Classification/Anomaly detection	Pass/Fail	9
Product Failure detection	Quality/Availability	Classification/Anomaly detection	Pass/Fail	8
Scheduling optimization	Performance	Regression	Cycle time	2
Waste reduction	Quality	Regression	Continuous measurements	2
Yield improvement	Quality	Regression	Continuous measurements	2
Preventive maintenance	Availability	Regression	RUL	2

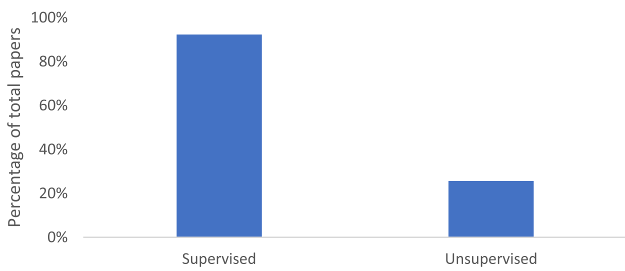

Fig. 8. Distribution of machine learning types.

4.4.2. RQ4.b What kind of machine learning tasks are addressed?

Fig. 9 shows that regression is the main task, which accounts for about 60% of all selected papers. There are about 20% of papers that applied classification and data reduction (i.e., dimension reduction) algorithms for data processing. For instance, Principle Component Analysis (PCA) is widely used to reduce the number of parameters for regression and classification problems.

4.4.3. RQ4.c What kind of machine learning algorithms are used?

Fig. 10 shows that the artificial neural network algorithm (ANN) is largely applied in production lines. ANN is the most frequently applied machine learning algorithm, including ten papers in 39 papers. Support Vector Machines (SVM) and Random Forests (RF) are in the second and third ranks. Decision Trees (DT), LSTM (long short-term memory), KNN (K-nearest neighbors), GBDT (gradient boosted decision tree), and CNN (convolutional neural network) are the other algorithms applied for production lines. CNN and LSTM algorithms are different deep learning algorithms.

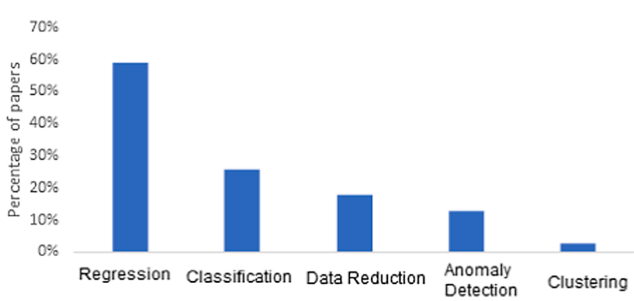

Fig. 9. Distribution of machine learning tasks.

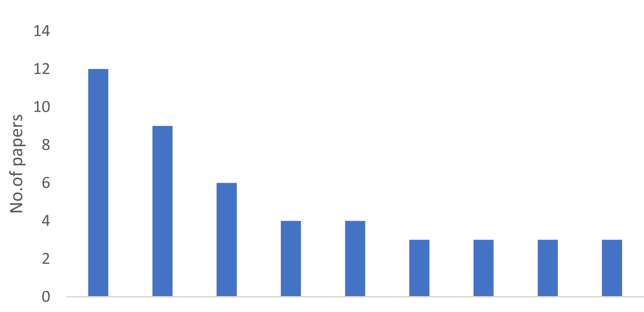

Fig. 10. Distribution of machine learning algorithms.

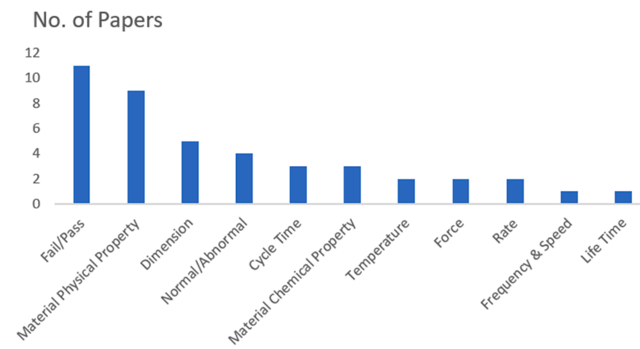

Fig. 11. Dependent variables used in machine learning models.

4.5. RQ5. What are the dependent and independent variables used in these models?

Fig. 11 shows that fail/pass is the most frequent dependent variable. The material physical property and dimension are the second and third output variables. The material physical property refers to parameters like mass, density, and strength. Material chemical property refers to chemical composition, battery capacity, and chemical concertation. Fig. 12 presents the categories of independent variables and the number of papers in which these were addressed. In this figure, features are divided into the following six groups: machinery operation, production line logistic parameters, raw material related parameters, product exit parameters, yield, and N/A (not applicable). The N/A category indicates that no information regarding the independent variables is provided in the paper.

Compared to the multi-class classification, binary classification is preferred more. Fail/pass is the major dependent variable type for classification, clustering, and anomaly detection tasks. Fail/pass

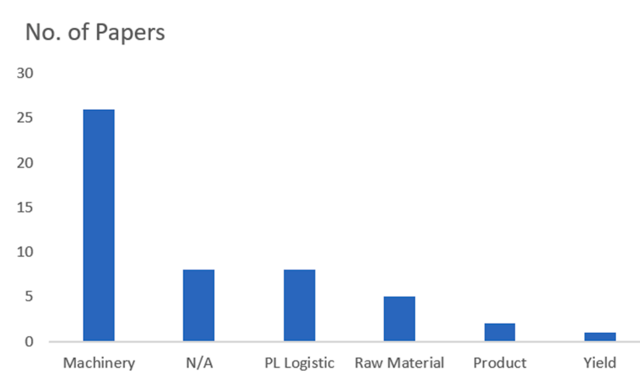

Fig. 12. Independent variables used in machine learning models.

prediction can be used for both quality prediction and availability prediction. The former predicts the pass/fail of products while the latter predicts the failure of motors in production lines. Also, production line lifetime prediction appears the least in papers.

5. Discussion

Computer and electronic product manufacturing, chemical manufacturing, and primary metal manufacturing are the top three areas in which machine learning was applied. The common features of these industries are high automation, high production volume, and complexity of products. Therefore, IoT technology is largely employed in these industries, and a huge amount of data is generated from these production lines. The complexity of the products and the abundance of data promote machine learning adoption. All production lines were classified based on four characteristics.

It was also observed that most of the production lines are single server working station without buffer. One reason for this observation might be the fact that only a subsystem is analyzed, and the buffer and multi-server stations are not considered in the paper. The analysis and design of the machine learning models are relatively easier in the case of a single server working station case. However, for in-depth analysis and better insight into the production environment, more research is required on the use of machine learning algorithms in the case of multi-server stations. Models on the multi-server stations that include buffer might require more complex machine learning algorithms, such as deep learning. Recently, deep learning, which is a sub-branch of machine learning, provided state-of-the-art results in many different domains, and as such, they can be applied in this context as well because a huge amount of data is produced in these production lines.

Supervised learning significantly overweighs unsupervised learning. This is due to the fact that more regression and classification tasks are applied in production lines. It also shows that data is abundant in production lines, and as such, supervised learning can be used to provide more accurate results. Regression and classification are the most common tasks for quality and cycle-time prediction. The quality and cycle time prediction is the dominant problem in selected papers. Clustering, anomaly detection, and data reduction are the main tasks that are addressed with unsupervised algorithms. Clustering and anomaly detection techniques are used in papers addressing fault diagnosis or preventive maintenance, and the availability of OEE is addressed. To improve the performance of machine learning models and shorten the development process of models, researchers might consider the new research trends in machine learning. Ensemble learning that combines the power of several individual machine learning algorithms for a particular problem can provide better performance compared to the performance of an individual algorithm (e.g., classification or regression algorithm). Transfer learning (a.k.a., domain adaptation) can also be investigated in this domain because a model built for a particular task can be used on a second related task with the help of transfer learning algorithms. Deep learning algorithms such as Convolutional Neural Networks (CNN), Long-Short Term Memory (LSTM), Recurrent Neural Networks (RNN), Deep Belief Network (DBN) can also be investigated to improve the performance of the machine learning-based models. When there is very limited labeled data, one approach in machine learning is to apply semi-supervised learning (SSL) algorithms that use unlabelled data together with the labeled data. Since labeling is a time consuming and expensive process in production lines, researchers might also consider developing novel models based on semi-supervised learning algorithms (e.g., classification or regression).

According to our analysis, ANN is the most frequently used algorithm. Presumably, there are two major reasons for the popularity of neural networks in the domain of production lines. First, the production line is a complex system, and neural networks can handle the sophisticated relationship between features and the dependent variable. Second, production lines can generate a huge amount of data, which is useful for neural networks. A larger dataset helps to achieve better results with neural networks. SVM and tree-based algorithms are also used frequently according to our results. Since deep learning algorithms are based on ANN algorithms, we expect to use more research on the use of deep learning in production lines. In a traditional ANN-based model, the number of hidden layers is generally equal to 1; however, there are many hidden layers in deep learning models. These hidden layers are not only fully-connected layers but also different types of layers, such as the convolutional layer and pooling layer in the case of deep learning models. The development of these models might require more effort and computing power, but the performance can be higher than the existing models.

OEE evaluates the performance of a production line, and it consists of three indexes, which are availability, performance, and quality. It was shown that quality prediction is the major area being applied with machine learning techniques. It suggests that a good product ratio is the most important aspect of a production line. The result also implies the fact that machine learning quality prediction may be more effective compared to the availability and performance prediction. The quality prediction only requires the data from the material and the individual machine and excludes the affection from the buffer and working station characteristics. It was also observed that there are just a few studies on the performance index. According to Equation (3), cycle-time is the most important parameter affecting the index of performance. However, the prediction of cycle time is affected by buffer zones and working station characteristics, which make it more difficult to make the prediction accuracy. There are 12 papers that addressed the availability index. Equipment preventive service and motor fault diagnosis are the two major research areas. According to our literature analysis, there is a research gap in the performance index of OEE, and more research is needed to address this index in detail. While more data might be required to develop novel models in this context, the benefits might be more substantial.

Quality is the most important OEE index, and quality-related problems are the dominant area in recent years. Product failure detection and quality optimization are two major components of quality control. For product failure detection, a high product quality pass rate not only increases the yield but also reduces material waste and energy consumption. Machine learning classifier is prevalently used to identify failed products. Binary classification is mostly applied to distinguish pass and fail products from production lines. With the development of IoT, more data is available not only to detect product failure but also to optimize quality. Any continuous values related to the product can be predicted by a machine learning regressor via input data collected from the production line. The machine learning model can help to determine the optimal production line settings to produce the highest quality products.

According to our SLR, availability is the second most studied OEE index in all papers. Accidental breakdown of production lines can bring tremendous loss to a factory as the output of the production line drops to zero. Fault diagnosis becomes important to identify the point of failure, and the repair can be arranged to restore the production process as quickly as possible. Both supervised, and unsupervised machine learning approaches are used, and most of the tasks are the identification of the failed operation pattern, which is a kind of binary classification problem, or an anomaly detection problem. While there are a lot of studies on the production line fault diagnosis, there are just a few studies on preventive maintenance. Preventive maintenance requires the prediction of Remaining Useful Life (RUL), which is difficult to measure in practice. However, preventive service can proactively reduce the number of breakdowns in production lines. The performance of machine learning applications in the area of preventive service can be improved with more data and novel algorithms. It is considered to be a potential area of research for the future. To improve the models for preventive service, deep learning and ensemble learning algorithms can be investigated by the researchers. One of the drawbacks of the machine learning models (e.g., ANN models) is that results are presented as black box decisions.

However, recently researchers in Artificial Intelligence (AI) focused on the development of interpretable and explainable models under the Explainable AI research topic (Samek, Montavon, Vedaldi, & Hansen, , 2019). This kind of model can also be beneficial in the production lines context because the stakeholders can better understand the system with the help of these explainable prediction models.

Another challenging issue in production lines is related to the imbalanced datasets. Most of the data points belong to one particular category, and a very limited number of data belongs to the other class. Especially for rare cases, most of the data points do not represent this specific situation, and therefore, specific algorithms will be required to balance the datasets. There exist several data balancing algorithms, such as SMOTE (Synthetic Minority Over-sampling Technique) and under-sampling. Researchers should also consider this type of algorithms in the case of imbalanced datasets.

For repeatable, improvable, and even refutable experiments, researchers need more public datasets in production lines. While there are some public datasets shared as part of competitions, they are still very limited, and we need more public datasets. Due to confidentiality and privacy reasons, companies do not wish to share their datasets; however, there are many techniques to prevent these concerns. Researchers might apply recent approaches developed in the privacy-preserving machine learning research field.

Cadavid, Lamouri, Grabot, Pellerin, and Fortin (2020) performed an SLR on the machine learning-aided production planning and control. They investigated the activities involved in these papers (e.g., feature extraction and model training), techniques (e.g., ANN), data sources (e.g., management, equipment, user, product, public, artificial), use cases, and characteristics of Industry 4.0 that are addressed in the study. According to their SLR study, smart planning and scheduling is the most applied use case, and ANN is the most applied algorithm. Apart from smart planning and scheduling use case, they specified the following use cases: smart maintenance, quality control, process control & engineering, inventory & distribution control, smart design of products and processes, and time estimation. They state that the use of IoT technologies for collecting data is complex, and it is not easy to modify the machine learning model based on manufacturing system changes.

Threats to the validity of our study are discussed as follows:

Construct validity: Construct validity evaluates whether the SLR reflects the degree to which it measures what it claims. Here we aimed to measure the insight from the existing literature and used automated search queries in various databases for this purpose. Although the database is an effective tool for literature search, it is also sensitive to the query phrasing. A slight change in the query can result in a very different result. Different databases have different query format and use numerous logical operators, which means that the query has to be slightly modified across databases. As a result of that, the query applied to the database may not find all relevant studies or even miss some of the related studies. For avoiding these threats, the query design is fully discussed among authors and tested via multiple trials. Each query search should return a reasonable number of papers. Later on, manual checking of the abstract of the papers is performed to make sure that the search result is valid. If most of the returned results are not relevant, the query is modified, and the search is performed again.

The second threat might be related to the process of result screening. Although the screening is based on the predefined criteria and assessment questions, it is not possible to eliminate the factor of personal subjective decisions during the scoring. Because the production line domain is very broad, which involves a wide range of knowledge, the authors carefully evaluated the papers, but there might be some papers that were not determined. The third threat is the data extraction. The data extraction form is predefined, and it is highly likely that some useful data might be missed in this extraction form. Also, some data is not easily accessed in papers. To make sure that all relevant data is extracted from research papers, our data extraction form is literately updated during the SLR process. New data is added if the data can be extracted from most of the papers and if it is useful to answer the research question. Some unnecessary data are removed to avoid misleading.

Internal Validity: Internal validity indicates the incomplete relationship between findings, which may introduce systematic errors. In this SLR study, all research questions are formulated to investigate the necessary elements for applying machine learning to the production lines. As machine learning elements are well-defined, the relationship between research questions and research goals is described properly.

External Validity: This SLR only investigates published papers, which applied machine learning techniques in production lines. It is likely that some novel machine learning methods, which have not applied yet in production lines, might have a potential for usage, but since they have not been published yet, they are not discussed in this paper.

Conclusion Validity: Reliability measures the reproducibility of the SLR. Our SLR follows the protocol of Kitchenham et al. (2009). The research question design, search process, screening criteria, and quality evaluation are performed based on this widely used protocol. Our SLR process is also discussed among authors to minimize the basis of each researcher. All conclusions are derived from the collected data based on tables and figures to avoid subjective interpretation of the results among researchers.

6. Conclusion

To the best of our knowledge, this is the first systematic literature review that explicitly discusses the application and the state-of-the-art of machine learning for production lines. A number of interesting insights can be derived from this study. First of all, the results of the study indicate that machine learning techniques have been widely adopted in a wide range of manufacturing domains to improve the OEE, and the included indexes of Quality, Performance, and Availability. The study shows that a focus has been provided on Quality and Availability in current literature. Machine learning has been widely used to solve several production line problems. Quality control and fault diagnosis are two major research directions in recent years, and machine learning approaches have been proved to be effective in these two areas. However, many problems are still not fully addressed, among which preventive maintenance is indicated as one of the important areas.

Machine learning is mostly applied in the domain of metal production and semiconductor industry, as the processes are highly complex, and more data is generated from this kind of production line. Data availability and data quality are the keys to the performance of machine learning. Supervised learning mostly achieves better results compared to semi-supervised learning and unsupervised learning approaches. More data per feature and balanced data can help to improve the performance of the machine learning models. However, good quality data is not always available for all kinds of problems. By using data pre-processing techniques and selecting appropriate algorithms, the machine learning model can provide systematic guidance to the production process.

As explained in the Discussion section, we identified the following future research directions based on our evaluation of the current literature.

- **Models for multi-server stations:** New machine learning models are needed for multi-server stations with buffer because most of the models are developed for the single-server case.
- **Deep learning-based models:** Deep learning algorithms achieved state-of-the-art results in many different domains, but they have not been investigated in production lines in detail yet. These algorithms can improve the performance of the existing models because a huge amount of data that can be generated in production lines is beneficial for these algorithms.
- **Ensemble learning / Transfer learning / Semi-supervised learning:** A lot of the studies applied traditional machine learning

algorithms. However, there are other approaches, such as ensemble learning, transfer learning, and semi-supervised learning, that can help to improve the performance of the models or simplify the development process of the models.

- **Models for performance index of OEE:** Most of the models were developed for the quality index of OEEE; however, performance index is also critical for production lines, and as such, we need new machine learning-based models for the performance index.
- **Explainable models:** Models developed with ANN algorithm are not interpretable and explainable because the ANN algorithm works black-box. However, we need new models that are explainable because stakeholders might wish to understand how the model reached a conclusion.
- **The data imbalance problem:** Datasets that represent rare cases are mostly imbalanced, which can be the case for many production lines. As such, we need to consider data balancing methods in conjunction with machine learning models. Also, there are some machine learning algorithms that already include a data balancing component, such as the RUSBoostedTree algorithm.
- **More public datasets:** The number of public datasets in production lines is very limited, and therefore, we need more public datasets that will pave the way for further research.

In our future work, we will build on the results of this SLR and aim to focus on the application of machine learning to the open and relevant research problems in production lines.

Appendix A

See Table 7.

Table 7
Data Extraction Form.

Extracted Elements	Content
General Information	ID, Title, Authors, Year, Type
OEE Index	Availability; Performance; Quality
ML Type	Supervised; Unsupervised
ML Task	Regression; Classification; Clustering; Dimension Reduction; Anomaly Detection
ML Algorithms	Random Forest; KNN; Neural Network; …
Industry Domain	Food; Metal; Electronics; Paper; Automobile; …
Target Process	Bread Kneading; Wafer polishing; Engine production; …
Buffer	Yes; No
Process Type	Continuous; Discrete
Production Volume	High; Low
Working Stations Characteristics	Single Server; Multi-Server
Dependent Variable	Temperature; Fail or Pass; Normal or Anomaly; …
Independent Variable	Input features
Production Line Problem	Failure detection; Quality Optimization; …

References

Bibliography

Bierbooms, R. (2012). Performance analysis of production lines: discrete and continuous flow models.

Cadavid, J. P. U., Lamouri, S., Grabot, B., Pellerin, R., & Fortin, A. (2020). Machine learning applied in production planning and control: A state-of-the-art in the era of industry 4.0. *Journal of Intelligent Manufacturing,* 1–28.

Dal, B., Tugwell, P., & Greatbanks, R. (2000). Overall equipment effectiveness as a measure of operational improvement–a practical analysis. *International Journal of Operations & Production Management, 20*(12), 1488–1502.

Kitchenham, B., & Charters, S. (2007). Guidelines for performing systematic literature reviews in software engineering.

Kitchenham, B., Pearl Brereton, O., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009). Systematic literature reviews in software engineering – A systematic literature review. *Information and Software Technology, 51*(1), 7–15. https://doi.org/10.1016/j.infsof.2008.09.009.

Kleinrock, L. (1976). *Queueing systems, volume 2: Computer applications* (Vol. 66). New York: Wiley.

Labor, U. S. D. o. (2019). Manufacturing: NAICS 31–33. from The Bureau of Labor Statistics https://www.bls.gov/iag/tgs/iag31-33.htm.

Luque, A., Peralta, M. E., de las Heras, A., & Córdoba, A. (2017). State of the Industry 40 in the Andalusian food sector. *Procedia Manufacturing, 13*, 1199–1205. https://doi.org/10.1016/j.promfg.2017.09.195.

Ngo, Q. H., & Schmitt, R. H. (2016). A data-based approach for quality regulation. *Procedia CIRP, 57*, 498–503.

Qian, F. (2017). Smart and optimal manufacturing: The key for the transformation and development of the process industry. *Engineering, 3*(2), 151. https://doi.org/10.1016/J.ENG.2017.02.016.

Riel, A., Kreiner, C., Macher, G., & Messnarz, R. (2017). Integrated design for tackling safety and security challenges of smart products and digital manufacturing. *CIRP Annals, 66*(1), 177–180. https://doi.org/10.1016/j.cirp.2017.04.037.

Synnes, E. L., & Welo, T. (2016). Bridging the gap between high and low-volume production through enhancement of integrative capabilities. *Procedia Manufacturing, 5*, 26–40.

Tummers, J., Kassahun, A., & Tekinerdogan, B. (2019). Obstacles and features of farm management information systems: A systematic literature review. *Computers and Electronics in Agriculture, 157*, 189–204. https://doi.org/10.1016/j.compag.2018.12.044.

Samek, W., Montavon, G., Vedaldi, A., Hansen, L. K., & Müller, K. R. (Eds.). (2019). *Explainable AI: interpreting, explaining and visualizing deep learning* (Vol. 11700). Springer Nature.

Primary Studies (Sources Reviewed in this SLR)

Can, B., & Heavey, C. (2016). A demonstration of machine learning for explicit functions for cycle time prediction using MES data. In 2016 winter simulation conference (WSC) (pp. 2500–2511). IEEE.

Lihao, W., & Yanni, D. (2018). A fault diagnosis method of tread production line based on convolutional neural network. In 2018 IEEE 9th international conference on software engineering and service science (ICSESS) (pp. 987–990). IEEE.

Wang, Z. H., Liu, Y. M., Gong, D. Y., & Zhang, D. H. (2018). A new predictive model for strip crown in hot rolling by using the hybrid AMPSO-SVR-based approach. *Steel Research International, 89*(7), 1800003.

Wang, Z., Cao, Z., Huang, R., & Zhang, J. (2017). A study on attribute selection for job shop scheduling problem. In 2017 13th IEEE conference on automation science and engineering (CASE) (pp. 1032–1037). IEEE.

Wang, P., Gao, R. X., & Yan, R. (2017). A deep learning-based approach to material removal rate prediction in polishing. *CIRP Annals, 66*(1), 429–432.

Golkarnarenji, G., Naebe, M., Badii, K., Milani, A. S., Jazar, R. N., & Khayyam, H. (2019). A machine learning case study with limited data for prediction of carbon fiber mechanical properties. *Computers in Industry, 105*, 123–132.

Milo, M. W., Roan, M., & Harris, B. (2015). A new statistical approach to automated quality control in manufacturing processes. *Journal of Manufacturing Systems, 36*, 159–167.

Vincent, B., Duhamel, C., Ren, L., & Tchernev, N. (2015). An industrial process optimization approach based on input and output statistical data analysis. *IFAC-PapersOnLine, 48*(3), 930–935.

Liu, X., Jin, J., Wu, W., & Herz, F. (2020). A novel support vector machine ensemble model for estimation of free lime content in cement clinkers. *ISA Transactions, 99*, 479–487.

Mulrennan, K., Donovan, J., Creedon, L., Rogers, I., Lyons, J. G., & McAfee, M. (2018). A soft sensor for prediction of mechanical properties of extruded PLA sheet using an instrumented slit die and machine learning algorithms. *Polymer Testing, 69*, 462–469.

Fritzsche, R., Richter, A., & Putz, M. (2017). Automatic adjustment of car body fixtures using artificial intelligence. *Procedia Cirp, 62*, 600–605.

Tsai, T. L., & Lee, C. Y. (2017). Data mining for yield improvement of photo spacer process in color filter manufacturing. *Procedia Manufacturing, 11*, 1958–1965.

Schnell, J., Nentwich, C., Endres, F., Kollenda, A., Distel, F., Knoche, T., & Reinhart, G. (2019). Data mining in lithium-ion battery cell production. *Journal of Power Sources, 413*, 360–366.

Oestersötebier, F., Traphöner, P., Reinhart, F., Wessels, S., & Trächtler, A. (2016). Design and implementation of intelligent control software for a dough kneader. *International conference on system-integrated intelligence*.

Pattarakavin, T., & Chongstitvatana, P. (2016). Detection of machines anomaly from log files in hard disk manufacturing process. In 2016 International conference on multimedia systems and signal processing (ICMSSP) (pp. 60–63). IEEE.

Luo, R. C., & Wang, H. (2018). Diagnostic and prediction of machines health status as exemplary best practice for vehicle production system. In 2018 IEEE 88th Vehicular Technology Conference (VTC-Fall) (pp. 1–5). IEEE.

Xiao, D., Huang, Y., Zhang, X., Shi, H., Liu, C., & Li, Y. (2018). Fault diagnosis of asynchronous motors based on lstm neural network. In 2018 prognostics and system health management conference (PHM-Chongqing) (pp. 540–545). IEEE.

Wang, Y., & Yang, R. (2017). Fault diagnosis system of emulsifier based on neural network theory. In 2017 Chinese Automation Congress (CAC) (pp. 3087–3091). IEEE.

Wu, S., Zhou, X., Cao, G., Shi, N., & Liu, Z. (2018). High-dimensional data-driven optimal design for hot strip rolling of microalloyed steel. *Steel Research International, 89*(7), 1800015.

Moldovan, D., Cioara, T., Anghel, I., & Salomie, I. (2017). Machine learning for sensor-based manufacturing processes. In 2017 13th IEEE international conference on intelligent computer communication and processing (ICCP) (pp. 147–154). IEEE.

Susto, G. A., Pampuri, S., Schirru, A., Beghi, A., & De Nicolao, G. (2015). Multi-step virtual metrology for semiconductor manufacturing: A multilevel and regularization methods-based approach. *Computers & Operations Research, 53*, 328–337.

Li, C., Wang, H., & Li, B. (2016). Performance prediction of a production line with variability based on grey model artificial neural network. In 2016 35th Chinese control conference (CCC) (pp. 9582–9587). IEEE.

Zhang, D., Xu, B., & Wood, J. (2016). Predict failures in production lines: A two-stage approach with clustering and supervised learning. In 2016 IEEE international conference on big data (big data) (pp. 2070–2074). IEEE.

Melhem, M., Ananou, B., Djeziri, M., Ouladsine, M., & Pinaton, J. (2015). Prediction of the Wafer quality with respect to the production equipments data. *IFAC-PapersOnLine, 48*(21), 78–84.

Besseris, G. J. (2015). Profiling multiple static and transient puff-pastry characteristics with a robust-and-intelligent processor. *Journal of Food Engineering, 164*, 40–54.

Liu, Y., Zhou, H., Tsung, F., & Zhang, S. (2019). Real-time quality monitoring and diagnosis for manufacturing process profiles based on deep belief networks. *Computers & Industrial Engineering, 136*, 494–503.

Wang, X., Liu, M., Ge, M., Ling, L., & Liu, C. (2015). Research on assembly quality adaptive control system for complex mechanical products assembly process under uncertainty. *Computers in Industry, 74*, 43–57.

Feng, X., Gao, Q., & Liu, M. (2018). Roller parameters prediction of steel tube based on principal component analysis and BP neural network. In 2018 Chinese control and decision conference (CCDC) (pp. 4627–4631). IEEE.

Corne, R., Nath, C., El Mansori, M., & Kurfess, T. (2017). Study of spindle power data with neural network for predicting real-time tool wear/breakage during inconel drilling. *Journal of Manufacturing Systems, 43*, 287–295.

Golkarnarenji, G., Naebe, M., Badii, K., Milani, A. S., Jazar, R. N., & Khayyam, H. (2018). Support vector regression modelling and optimization of energy consumption in carbon fiber production line. *Computers & Chemical Engineering, 109*, 276–288.

Principi, E., Rossetti, D., Squartini, S., & Piazza, F. (2019). Unsupervised electric motor fault detection by using deep autoencoders. *IEEE/CAA Journal of Automatica Sinica, 6*(2), 441–451.

Karagiorgou, S., Vafeiadis, G., Ntalaperas, D., Lykousas, N., Vergeti, D., & Alexandrou, D. (2019). Unveiling trends and predictions in digital factories. In 2019 15th International Conference on Distributed Computing in Sensor Systems (DCOSS) (pp. 326–332). IEEE.

Mangal, A., & Kumar, N. (2016). Using big data to enhance the bosch production line performance: A kaggle challenge. In 2016 IEEE International Conference on Big Data (Big Data) (pp. 2029–2035). IEEE.

Pani, A. K., & Mohanta, H. K. (2016). Online monitoring of cement clinker quality using multivariate statistics and Takagi-Sugeno fuzzy-inference technique. *Control Engineering Practice, 57*, 1–17.

Duhamel, C., Vincent, B., Tchernev, N., & Ren, L. (2015). Support Vector machine and Monte Carlo simulation for robust optimization of industrial processes. In 2015 International Conference on Industrial Engineering and Systems Management (IESM) (pp. 988–997). IEEE.

Munirathinam, S., & Ramadoss, B. (2016). Predictive models for equipment fault detection in the semiconductor manufacturing process. *IACSIT International Journal of Engineering and Technology, 8*(4), 273–285.

Kim, J., Han, Y., & Lee, J. (2016). Data imbalance problem solving for smote based oversampling: Study on fault detection prediction model in semiconductor manufacturing process. *Advanced Science and Technology Letters, 133*, 79–84.

Wen, L., Li, X., Gao, L., & Zhang, Y. (2017). A new convolutional neural network-based data-driven fault diagnosis method. *IEEE Transactions on Industrial Electronics, 65*(7), 5990–5998.

Razavi-Far, R., Farajzadeh-Zanjani, M., Zare, S., Saif, M., & Zarei, J. (2017). One-class classifiers for detecting faults in induction motors. In 2017 IEEE 30th Canadian conference on electrical and computer engineering (CCECE) (pp. 1–5). IEEE.