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PRODUCTION MANAGEMENT

Digital-based production: introduction and fields of application

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Abstract
This special issue on "digital-based production" gives an overview about the current research on the integration of digital technologies into production processes and their fields of application. It covers topics from Industry 4.0, artificial intelligence and data analytics to the Industrial Internet of Things and Cyber-Physical Production Systems. This issue offers valuable insights for those interested in improving production efficiency, quality, and sustainability through digital technologies. In this foreword, we describe promising application fields of digital-based production and classify the submitted articles accordingly.

Keywords Digital-based production · Digital technology · Application fields · Classification

1 Introduction

Digital-based production is an integrated approach that uses digital technologies to monitor, analyse, simulate, and improve production processes, machines, equipment, and complete systems. In recent years smart sensors, new communication standards, cyber-physical systems, the Industrial Internet of Things (IIoT) and Artificial Intelligence (AI) are starting to pervade manufacturing systems [1]. The increased use of these technologies in manufacturing processes has led to a greater availability of data. At the same time, the cost of computing power, storage, and hardware is decreasing. In combination with an improved access to almost ready to use Machine Learning (ML) algorithms, this opens up new and promising fields of application for the manufacturing industry.

2 Application fields in digital-based production

The various use cases in relation to digital-based production can be classified into four application fields, according to [1]: condition monitoring and predictive maintenance, quality management, process monitoring and optimization and energy monitoring and flexibility.

Condition monitoring is the continuous monitoring of a machine or system's performance and condition, with the aim of detecting any potential problems or issues. The collected data is analysed to identify trends or deviations from normal behaviour and to support root cause problem solving [2]. Predictive maintenance techniques anticipate equipment failures, the prediction of the remaining useful lifetime (RUL) and allow the recommendation of appropriate measures to improve equipment uptime. In particular, the prediction of the RUL of machines and components can – if accurately assessed – provide valuable information for maintenance planning and decision-making [3]. An example for a direct approach on tool condition monitoring and lifetime assessment, give Jourdan et al. (2021) who have developed a system that can measure the degree of wear of a saw blade during operation [4]. For this purpose, a high-resolution camera takes images of the saw blade, which will subsequently be analysed by computer vision and an ML algorithm to detect the edge of the saw blade and the tips of the saw teeth. The degree of wear is then determined by the difference in length of the non-worn saw tooth to the measured actual condition.

In the context of quality management, predictive quality is expected to enhance classical quality assurance which is essentially based on measuring parts today. Predictive quality allows the determination of quality characteristics of a part or a product based on process and machine data without a dedicated measuring operation on the part itself.

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Furthermore, the detection of abnormalities based on process data allows real-time correction by modifying process or control parameters [5]. However, obstacles such as costs and adequate data acquisition pose challenges. In another example, drilling holes are classified by analysing process data using a random forest classifier [6]: While it is not possible to distinguish between the classes OK and NOK with conventional analysis, the ML approach allows this classification.

Process monitoring refers to the use of various tools and techniques to continuously monitor the behaviour and performance of a process plant or system, with the goal of detecting and diagnosing abnormal events or faults in real-time [7]. Consequently, the aim of process optimization is to improve the overall efficiency and productivity of the process by identifying and eliminating waste, minimizing downtime, and optimizing resource utilization. The application field process monitoring and optimization can be classified into the categories process, production planning and scheduling and value stream [1]. To improve productivity, quality, and efficiency, comparing collected data to optimized Key Performance Indicators (KPIs) is recommended. Intelligent machining parameter optimization is used to minimize machining time, improve productivity, and ensure product and tool quality, using sensor technology, high-frequency image data, and Computer-Aided Manufacturing (CAM) for in-process monitoring and control. Data-driven simulation-based optimization provides real-time decision-making based on the current system state but requires a well-structured data exchange framework. Via web-based applications, process data and analyses can be accessed from anywhere without having to pass through the automation pyramid. Digital twins represent a replica of physical assets in the real factory and allow its simulation, control, and improvement. In contrast, a digital shadow is a reflection of the relevant data in a factory. Intelligent algorithms such as genetic algorithms can optimise various manufacturing problems, and data process mining can analyse complex value streams that include product variety and dynamic changes in production. For instance, Ziegenbein (2022) discusses the potential of integrating ML methods into industrial production processes to achieve predictive quality, a better understanding of processes, development of knowledge, and savings through process optimization [8]. Further use cases were implemented in the process learning factory "Center for Industrial Productivity" [9], such as a digital twin of a value stream, through which relevant data in a database is used with a backflow of information for decision-making [10].

Sustainability in general refers to the ability to meet the needs of the present generation without compromising the ability of future generations to meet their own needs [11]. In the context of manufacturing, sustainability also includes improving resource efficiency, reducing energy consumption, increasing the use of renewable energy, and promoting the circular economy by designing products and processes that reduce waste and extend product lifecycles. According to the International Organization for Standardization (ISO), energy efficiency as a part of sustainability in manufacturing is "the relationship between the energy inputs and the outputs in the manufacturing process, including energy losses" [12]. Digitalization and data analysis have the potential to improve energy efficiency and sustainability in industry. For instance, the ETA learning factory at PTW focuses on increasing transparency and optimizing energy systems through data-driven methods [13]. Energy metering points can be used to collect data to feed into an energy prediction model that has been developed by Sossenheimer et al. (2020) and is used to forecast energy demand [14], avoid load peaks and align energy demand with energy supply: Advanced signal processing and ML techniques, such as short-term load forecasting, enable efficient energy purchasing and cost reduction [15]. Energy-adaptive production planning and optimized supply system control can result in significant energy savings with the use of optimization techniques like genetic algorithms or deep reinforcement learning [16].

In Fig. 1, the application fields are summarized based in the categories use-case, data and information, digitalization of physical quantities, integration and communication, signal processing and analysis [1, 17].

The application fields illustrate current fields of research and practical application in the field of digital-based production. However, pure technical progress does not usually lead to the spread of new technologies. Corresponding business models are also required, especially for ML applications [18]. Dimensions like value proposition, value creation, revenue mechanism, and customer benefit need to be addressed systematically to successfully anchor a business model [19]. Data-based business models may involve value creation through ML algorithms that can analyse data from various sources, such as sensors, equipment, and production lines, to identify patterns and make predictions. The revenue mechanism in this scenario could involve selling the ML solutions to other manufacturers, final customers or using them internally to improve operational efficiency and increase profitability. Finally, the customer dimension addresses the needs and preferences of different stakeholders within the manufacturing organization, such as plant managers, production engineers, and the aspects of acceptance and usability.

3 Classification of articles based on the application fields

In the following, the articles of this special issue are classified according to the application fields shown. For this purpose, the articles were categorized:

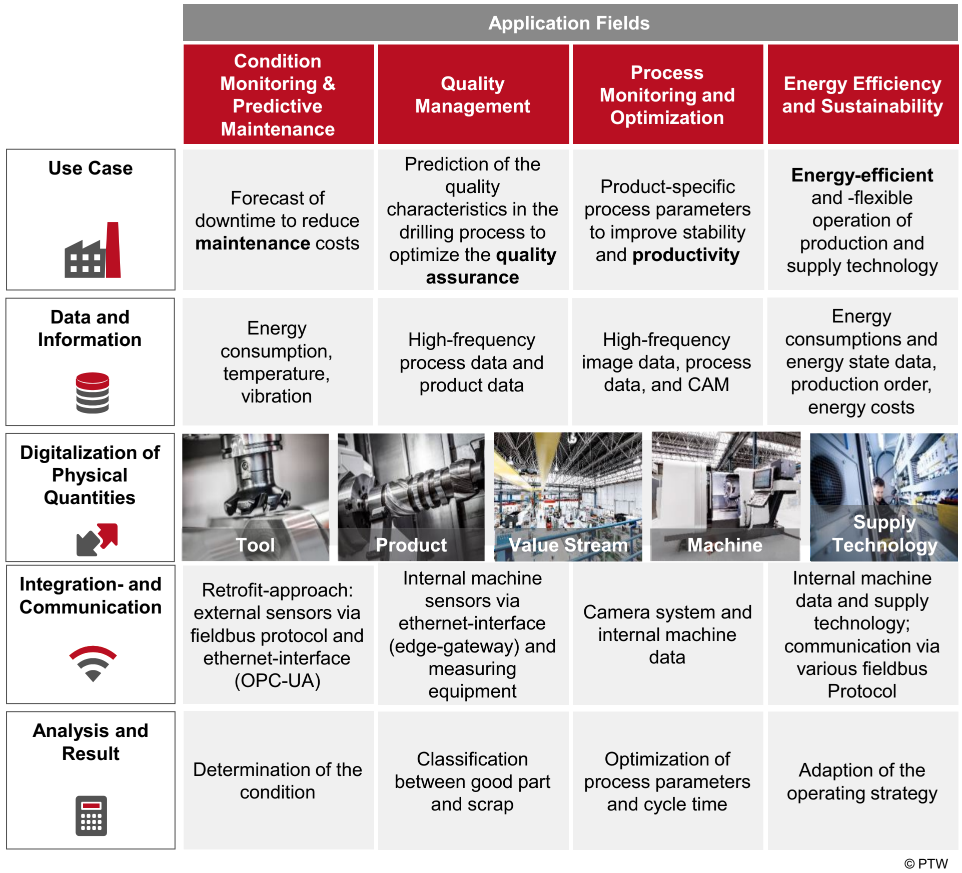

Fig. 1 Application fields of digital-based production, based on [1, 17]

- In the field of condition monitoring and predictive maintenance, the articles cover the topics optimization and prediction in tool management, the evaluation of data quality using machine learning algorithms and the prediction of missing KPIs.
- In the field of quality management, defects to hybrid glass fiber components are evaluated, quality for milling processes is predicted and workshop operation status for quality control in discrete manufacturing is evaluated.
- In the field of process monitoring and optimization, product and process configurations are considered using data analytics, varying time series representation learning techniques and their performance evaluation in clocked manufacturing are studied and industrial cast aluminium alloys processes are analysed using machine learning.
- In the field of energy efficiency and flexibility, a data-based methodology for evaluating the potential of industrial energy systems for connecting to district heating systems is developed, a method for measuring process-specific induced strains and mechanical stresses of the machined workpiece as well as temperature gradients in the cutting tool is presented and the modular lightweight design of robot systems for aircraft production was further developed.

Table 1 summarizes the result. This classification is intended to assist the reader of this special issue in selecting publications.

The integration of cyber-physical systems into digitized production has changed and will change manufacturing in many ways. The ability to bridge the gap between the physical and the digital world will enable real-time monitoring, control, and optimization of production processes. This will enable greater flexibility, efficiency, and agility in manufacturing, improve product quality, and reduce waste. If models of machines, processes or entire value streams are fed with real data in real time, it will be possible to detect deviations before they occur. Simulation, among other things, can help here. On the basis of such digital process twins, it will then be possible to make qualified decisions from the process image in order to proactively steer a machine or a process in the desired direction. To be successful in the long run, digital solutions must always consider the end user, their specific competence set and the application context.

Table 1 Classification of the publications in this special issue

Application field	Publication
Condition monitoring and predictive maintenance	Tool management optimisation through traceability and tool wear prediction in the aviation industry
	Data quality evaluation for smart multi-sensor process monitoring using data fusion and machine learning algorithms
	Graph-based prediction of missing KPIs through optimization and random forests for KPI Systems
Quality management	Function-oriented defect assessment in hybrid sheet molding compound tensile specimen
	Quality prediction for milling processes—Automated parametrization of an end-to-end machine learning pipeline
	Research on the evaluation method of the operation status of digital workshop in discrete manufacturing industry
Process monitoring and optimization	Creation and validation of systems for product and process configuration based on data analysis
	Learning efficient stroke representations in clocked sheet metal processing: theoretical and practical evaluation
	Investigation of industrial die-cast Al-alloys using X-ray micro-computed tomography and machine learning approach for CT segmentation
Sustainability and energy efficiency	Cascaded heat merit order for industrial energy systems to evaluate district heating potential
	In-situ characterization of tool temperatures using in-tool integrated thermoresistive thin-lm sensors
	Modular Lightweight Robot System for Aircraft Production Using a Generic OPC UA Skill Concept

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Data availability Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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