Eng. Sci., 2024, **29**, 1088

Engineered Science
DOI: https://dx.doi.org/10.30919/es1088

Role and Applications of Artificial Intelligence and Machine Learning in Manufacturing Engineering: A Review

Sara Bunian,[1,#] Meshari A. Al-Ebrahim[2,*,#] and Amro A. Nour[3,#]

Abstract

The use of artificial intelligence (AI), machine learning (ML), embedded systems, cloud computing, Big Data, and the Internet of Things (IoT) is influencing the paradigm shift toward advanced technologies and highly efficient manufacturing processes in Industry 4.0. The need for AI is increasing day by day due to the rapid progress contributed by the successful utilization of intelligent and learning machines. AI is implanted in smart manufacturing to solve crucial sustainability issues and to optimize the supply chain, use of energy and resources, and waste management. Industry 4.0 is striving for customer-driven manufacturing capabilities for enhanced agility, sustainability, and productivity. AI and ML are primarily used in the optimization and monitoring of modern industrial processes. Industrial AI system research is a multidisciplinary field with contributions from ML, robotics, and IoT. Industrial AI develops, validates, deploys, and maintains solutions for sustainable manufacturing. Because of the rise in cloud computing and a significant decrease in data storage costs, a massive amount of information and data can now be stored and transmitted to ML and AI algorithms to streamline and automate different processes of an organization. The framework of smart manufacturing and Industry 4.0 is based on smart process design, monitoring, control, scheduling, and industrial applications. Smart manufacturing encompasses a broad range of domains, originally referred to as IoT-based technologies.

Keywords: Artificial intelligence; Manufacturing engineering; Machine learning; Industry 4.0; Sustainability; Embedded systems; Internet of Things (IoT); Robotics; Mechanical engineering.
Received: 10 October 2023; Revised: 03 November 2023; Accepted: 12 November 2023.
Article type: Review article.

1. Introduction

The sustainability and quality of the manufacturing processes require innovative and smart production units. The use of artificial intelligence (AI), machine learning (ML), embedded systems, cloud computing, Big Data, and the Internet of Things (IoT) is influencing the paradigm shift toward advanced technologies and highly efficient manufacturing processes. As John McCarthy, known as the father of AI, said, “artificial intelligence is the science and engineering of making intelligent machines, especially intelligent computer programs”.[1] AI simulates human capacities such as learning and problem-solving. There are various categories of AI, including ML, programming, data mining, genetic algorithms, neural networks, artificial life, and theory of computation. AI is in widespread use across engineering, education, science, medicine, economics, finances, marketing, and other fields. Due to the rapid progress contributed by the successful utilization of intelligent and learning machines, the need for AI is increasing day by day. AI is implanted in smart manufacturing to solve crucial sustainability issues and to optimize the supply chain, use of energy and resources, and waste management. Environmentally friendly manufacturing can be implemented via AI optimization of manufacturing processes. As head for sustainability services of PricewaterhouseCoopers, Hendrik Fink said in 2019, “If we properly incorporate artificial intelligence, we can achieve a revolution with regard to sustainability. AI will be the driving force of the fourth industrial revolution”.[2]

Industry 4.0 is striving for customer-driven manufacturing capabilities for enhanced agility, sustainability, and

[1] *Kuwait Petroleum Corporation (KPC), Oil Sector Complex, Shuwaikh Industrial 1, Block 1 St 74, Safat 13126, Kuwait.*
[2] *State Audit Bureau (SAB), Shamiya 71661, Kuwait.*
[3] *American University of Kuwait (AUK), Safat 13034, Kuwait.*
[#] *These authors contributed to this work equally.*
**Email:* meshari.alebrahim@gmail.com (M. A. Al-Ebrahim)

productivity. AI and ML are primarily used in the optimization and monitoring of modern industrial processes. ML is a subset of AI that is related to data accumulation for automatic learning processes and the development of a subsequent knowledge base. AI combined with ML can shape a comprehensive data monitoring system supported by cyber-physical systems (CPS), IoT architectures, and Big Data analysis capabilities in manufacturing processes. The technological paradigms shift for Industry 4.0 is mainly data-driven, and the exploitation of important data can equip industries with significant gains in productivity, efficiency, and quality. ML has a critical role to play in process optimization within modern industries. AI can improve manufacturing performance by using analytically capable tools and creating new services that are smart enough to run autonomously. Beyond improving the core manufacturing process, smart manufacturing involves real-time optimization of the whole value chain. CPS's modify the manufacturing processes with such tools as self-awareness, self-monitoring, and self-optimization. In Industry 4.0, AI is a key technological advancement for redefining manufacturing processes and conventional business models. AI systems can sense the environment, process relevant data, solve complicated problems, and continuously learn to improve their responses.

Industrial AI system research is a multidisciplinary field with contributions from ML, robotics, and IoT. Industrial AI develops, validates, deploys, and maintains solutions for sustainable manufacturing. The integration of such fields grants manufacturing systems the capacity to acclimatize and find solutions within predetermined boundaries via autonomy in actions. Managers, scientists, and executives can take advantage of the accessibility of AI to boost organizational productivity. Because of the rise in cloud computing and a significant decrease in data storage costs, massive amounts of data can be stored and transmitted to ML and AI algorithms to streamline and automate different organizational processes. Furthermore, equipment and machines are upgrading to intelligent levels. Intelligent manufacturing uses advanced AI technologies to accomplish smart, flexible, and reconfigurable manufacturing and machine processes to meet the changing demands of a dynamic global market. Using smart sensing, advanced materials, adaptable decision-making tools and models, data analytics, and intelligent devices, the complete product lifecycle and value chain improves. The Intelligent Manufacturing System (IMS) is an achievement of this idea;[3] this is the manufacturing system of the future, adopting the latest models and efficient methodologies to evolve conventional manufacturing processes into smart systems.[4]

The Ministry of Education and Research in Germany stated[5] that "Industry is on the threshold of the fourth industrial revolution. Driven by the internet, the real and virtual worlds are growing closer together to form the Internet of Things." IoT is a network system that provides tools for smart device communication and interconnectivity. Two distinct and crucially significant variables are required in IoT configuration: a complete set of tags and sensors, used to gather data generated from various stages and processes; and data transmission software protocols to move and store this data to a central server.[6] The CPS manages and analyzes the data transmitted through this interconnected network of systems between the physical and computational units. Advanced networks and systems integrate IoT to enable real-time information gathering along with post-data feedback.[7] The various systems of CPS are data collection, smart sensing, autonomy, and feedback mechanisms. Additionally, an important aspect of Industry 4.0 is cloud computing, used to manage and store real-time data and provide data storage and Big Data analytics. Analyzing and storing large flows of data are among the most significant applications of Industry 4.0.

Industry 4.0 has caught the attention of both industry and academia. Different research studies have focused on Industry 4.0 and its applications, trends, framework, and challenges. However, only a handful of studies have tried to connect Industry 4.0 with the progress in smart manufacturing by integrating AI and ML. There is a need to compare the findings of industrial and academic research regarding smart manufacturing and to understand the role of AI and ML in Industry 4.0. This is the primary motivation for this review. In this context, Table 1 provides an overview of the integration of technology within industries, which the authors will use to frame the discussion on the topics of AI and MI, smart manufacturing, process optimization, process control, fault detection, computing, and data storage.

2. AI in Smart Manufacturing and Industrial Evolution

The framework of smart manufacturing and Industry 4.0 is based on smart process design, monitoring, control, scheduling, and industrial applications. Fig. 1 illustrates the key components of this framework. Smart manufacturing encompasses a broad range of domains, originally referred to as IoT-based technologies. Smart manufacturing incorporates techniques related to CPS, Internet of Services (IoS), Big Data and analytics, and advanced robotics. The proliferation of CPS/IoT and smart objects, by means of which products have become accessible and networked, has enabled data-gathering to support precise targeting for timely and effective decision-making. Moreover, the combined effect of real-time data,

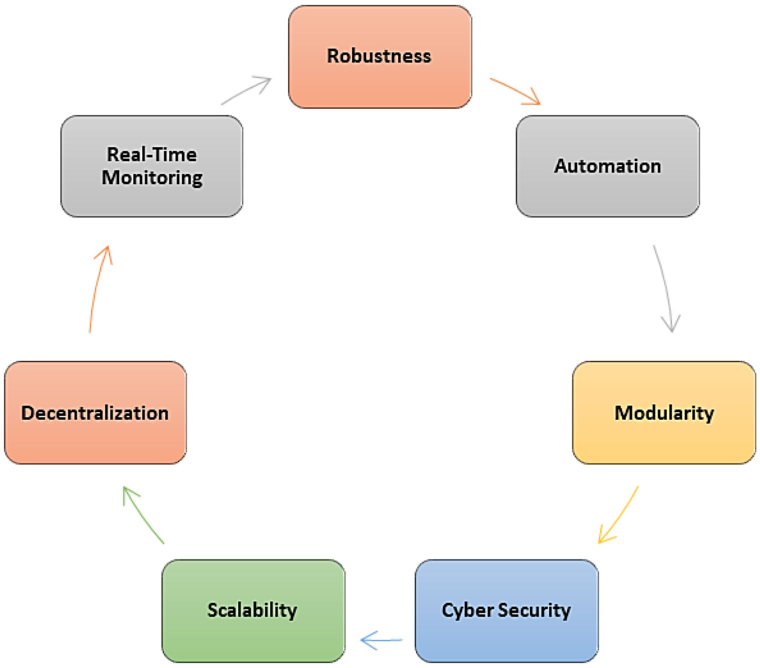

Fig. 1 Advantages of integrating smart manufacturing and AI in industrial processes.

Table 1. Integration of technology within industries.

Technology Level	Description	Industrial Integration
Level 0	Human-centered manufacturing process without any role of AI and ML.	Industrial process with fixed operations that are predesigned and planned.
Level 1	Human-centered operations with selected assistance.	All human control. AI and ML assistance can only suggest improvements to optimize costs, utilities, and production, which machine operators approve.
Level 2	Semi-autonomous operations within well-defined limits and certain areas.	Autonomous processes designed and programmed by humans. AI can make changes based on real-time data to optimize production, but only within predesigned limits.
Level 3	Prediction and warning systems to detect anomalies in the production and report the issues to machine operators, who take the appropriate decision.	AI can adjust based on predefined boundaries of the manufacturing system. The machines are equipped with digital sensors to predict and forecast potential issues.
Level 4	Better adaptability of the system. Limited human interaction with autonomous and smart manufacturing.	Constant learning to optimize the subsystems of a large manufacturing system within specified boundaries. Features of this level include implementing solutions, control, monitoring, and optimization.
Level 5	Completely autonomous systems with direct linkage with other autonomous processes.	Extreme adaptability to various situations. In case of emergency, these systems can go into Safe Mode. These systems can make autonomous decisions and change system boundaries accordingly.

human factors, smart AI algorithms, and data analytics enhances manufacturing capabilities.

2.1 Process design

The newest technologies, including augmented reality (AR) and virtual reality (VR), have upgraded traditional manufacturing processes to smart and efficient manufacturing. Hybrid prototypes have enabled the integration of VR into manufacturing, while computer-aided design and manufacturing software can directly communicate in real time with physical systems through AR, VR, and CPS. Modern engineering practices are changing to incorporate these smart manufacturing systems to achieve the ultimate of goals of automation.[8]

2.2 Virtual and augmented reality

VR refers to computer-generated visuals that simulate real-world events and activities, providing users of the technology with the sensation of being physically present in a virtual world. VR is being used to train technical staff for smart manufacturing. Through VR, engineers and technicians encounter industrial challenges and details of manufacturing processes. VR saves on the costs of prototyping and testing by forming a virtual environment to simulate the actual process and product.[9] Visualization of digital processes in manufacturing and testing in virtual simulations enables faster innovation and more efficient product cycles. Meanwhile, AR is a virtual environment created to analyze real-world manufacturing problems and solutions. The process, based on training, validation of data, and product testing, offers significant benefits in terms of time and cost savings.[10]

2.3 Smart machines

The integration of smart tools, robots, and manufacturing agents has revolutionized manufacturing. Agent-based systems can act autonomously and make certain decisions based on real-time data. Similarly, CPS systems record and process data through cloud computing to optimize smart machine tools. Smart systems have built-in quality control mechanisms, making post-processing quality checks unnecessary.[11]

2.4 Smart monitoring

Monitoring systems in smart manufacturing are critically important for day-to-day operations, scheduling, and maintenance of machines. A sensing network spread across the entire manufacturing line records data such as temperature, vibrations, speed, and energy consumption. Data visualizations and CPS systems monitor all manufacturing processes and can issue alerts in the event of abnormalities. Multi-task agents, CPS, cloud computing, and IoT provide the necessary tools for these massive data analytics.[12]

2.5 Smart control

CPS's and multi-agents enable better control over the machines used in Industry 4.0. Smart control executes tasks through cloud computing and operates and monitors these tasks remotely. Decisions can be made to optimize manufacturing and increase process efficiency. Industrial AI, in combination with the modern internet, has been a backbone of smart industry, due to rapid progress and growth in mobile internet devices, cloud computing, and mobile communication technologies (*e.g.*, 5G). Industrial AI integrates with generic AI to accomplish novel applications like designing innovative models, smart manufacturing, improved decision-making, and efficient allocation of resources. Industrial AI enables smart industries and machines to autonomously perceive, execute, learn, adapt, and decide, enabling the system to work on a variety of industrial tasks and adjust according to ever-changing industrial scenarios. Process efficiency, improved product quality, and optimal use of resources and equipment are thereby enabled. The ability to collect industrial Big Data through internet and cloud computing allows smart industries and businesses to optimize their processes, thereby supporting their endeavors in research and development of modern AI technologies, including the below:

2.5.1 Industrial revolution

The first industrial revolution started in 1760 in response to the boom in the textile industry. Industries witnessed significant growth in terms of opportunities, investments, and outputs. Railway, mining, coal, and iron industries were the benefactors of this growth opportunity. Agriculture-based economies shifted to industries for economic and material gain.[13]

Energy sources such as gas, oil, and coal gave rise to the second industrial revolution, which saw the development of new inventions and manufacturing tools. New industrial processes enhanced the output of steel production, fertilizers, dyes, engines, ships, chemicals, clothing, and transportation. Aiding this revolution were modern communication technologies, such as the telephone and telegraph. The energy development and distribution framework was laid out to integrate electricity into the modernization of society.[14]

The third industrial revolution started right after World War II, with the additions of Programmable Logic Controls (PLCs) and robots for process automation. Telecommunication, processors, computing, transistors, and computers have seen massive research and development and opened new opportunities for sustainable industrial growth. This third revolution brought unparalleled changes to information technologies and electronics for automation.[15]

In 2011, German experts coined the term "Industry 4.0" to describe the fourth industrial revolution.[16] This fourth revolution is based on the integration of cloud computing, IoT, AI, ML, and real-time data collection for business analytics. Industry 4.0 not only connects different manufacturing systems and processes but also makes smart decisions based on AI algorithms. This includes AR, VR, and process automation for manufacturing. Nevertheless, it may be some time before conventional manufacturing systems are fully

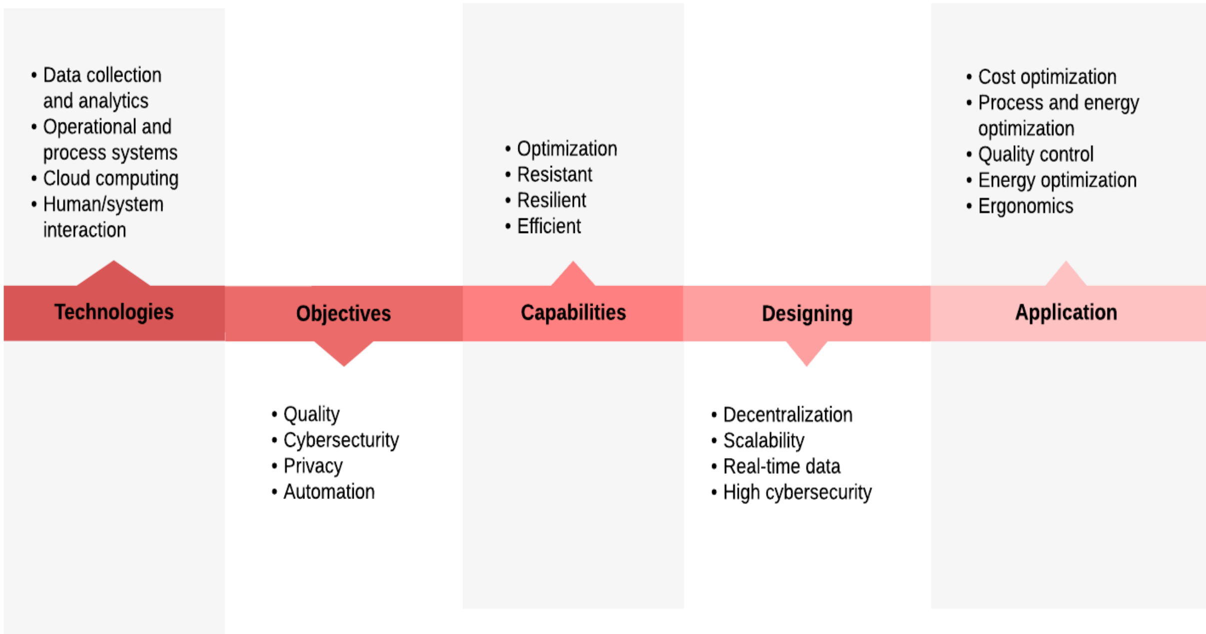

Fig. 2 Framework and system design for industrial AI.

upgraded and adopted to an Industry 4.0 infrastructure.[13]

3. Applications of ML and AI in manufacturing industries

In the context of modern industrial processes, AI is instrumental in addressing challenges associated with smart manufacturing. Within the spectrum of AI and ML, a prominent subcategory, has made significant inroads into the contemporary industrial sector. The evolution of manufacturing processes has led to a growing demand for datasets harnessed by ML models. These datasets fuel applications such as deep learning, data analytics, and automation. Neural networks play a pivotal role in modern industry, where they continuously monitor processes, detect anomalies, and thereby contribute to enhancing manufacturing efficiency.[17] The framework and system design for industrial AI, illustrated in Fig. 2, provides a visual representation of these critical components.

3.1 Process optimization

Data analytics combined with ML can provide optimal parameters in manufacturing, enabling the process of optimization and improvement. In the coming decade, the intersection of ML and process optimization will develop significantly, leading to manufacturing and industrial analytics for faster customized and mass production with little or no waste. Rønsch *et al*.[18] examined the efficient utilization of real-time data sets to improve injection molding processes, collecting data from 100+ molding machines. Their study investigated the process of integrating ML to achieve high process accuracy. The research found that existing manufacturing data did not represent and detect the variance in raw material that affects the quality of products, but that additional monitoring sensors could be used in molding to collect better raw data. The study collaborated with industries to have reliable and real-time data.

Lorenz *et al*. [19] presented an innovative use of a data-driven approach to boost productivity in make-to-stock product manufacturing. The implemented approach used process mining as a tool for dynamic mapping and complex analysis of manufacturing processes that required variation for automations in a systematic way to enhance productivity. The study validated the results experimentally, using this model as a test case for a major producer of sanitary items. The results offered ideas for the manufacturers to optimize the production processes. Zangaro *et al*.[20] described and analyzed a supervised and learning-driven strategy for the line feeding problem (LEP) by using the regression tree and classification technique. The suggested method used different components, tools, and real-time manufacturing processes data as input to build a decision tree that recommended a line feeding mechanism for the optimization. Furthermore, for scenarios with no clear solution, they defined a repair strategy that delivered feasible solutions and ideas with reasonable average cost addition. The suggested method predicted and optimized the line feeding mode accurately. These studies align with the themes presented in Table 2, which focuses on 'Progress in hardware, data analytics, and software in integrating AI for industrial applications.' The methodologies discussed in the table are relevant to the utilization of AI and data analytics in industrial contexts.

Table 2. Progress in hardware, data analytics, and software in integrating AI for industrial applications.

Parameters	Advances in AI	Industrial AI
Hardware	Fast computing, cloud computing, faster GPUs and CPUs	Smart manufacturing, autonomous processes, robotics
Data Analytics	Data gathering and analyzing	Sensors and interconnected process for data transfer
Software	Deep learning, AI and ML systems	Learning, digital twins, simulations

3.2 Human and robot collaboration

Industrial AI offers significant potential to strengthen human–robot collaboration and give support to existing human-centric jobs on the production line, whether by increasing operator safety and welfare or by optimizing tasks in a more efficient manner. Current potential for Industrial AI in the manufacturing sector includes workforce training, planning, monitoring, assistance, and collaborations with robots. Given this potential, human–robot collaboration must be studied further to enable stakeholders within manufacturing to fully utilize the advantages of Industrial AI. By using AR or VR, human–robot interaction may facilitate and improve such manufacturing processes as maintenance, assembly, and remote diagnostics.

3.2.1 Operations and planning

Various industries have complex work sequences, and any slight issue can have a significant impact on process efficiency, cost, quality, time, and waste management. The operation of any machine consists of various tasks and requires different tools. AI and ML can be used to operate and plan these complex work sequences through neural networks and algorithms. Research studies have used various AI and ML models to plan, optimize, and increase the efficiency of manufacturing processes.

Rentsh *et al.*[21] employed fitness function algorithms and genetic models to optimize resource and energy efficiency in production line designs and process operations. Brik *et al.*[22] classified employees and workers in a model based on the disruption model, utilizing supervised techniques such as regression, random forest (RF), and decision-making tree techniques. In choosing an algorithm, the study evaluated the classification accuracy of a process and considered modeling and prediction times. Using completely random trees, gradient-boosting trees (GBT), and RF, Walther *et al.*[23] forecasted and predicted the factory load in advance. Before selecting an algorithm, researchers carried out selection or detection by modeling it and eliminating repetitive features. The study implemented the model with a feature of engineering that makes use of moving averages to improve the performance and efficiency of the selected algorithms.

3.2.2 Monitoring

Monitoring is one of the most important processes to optimize manufacturing and gather real-time data for analytics. Industries need constant monitoring of the manufacturing process to identify faults and rectify or even predict the fault to avoid undesirable results. ML can train the models by feeding the data of these complex processes; based on the input data, these models can then predict future faults. Smart sensors can gather data that is, otherwise, impossible to gather. Smart monitoring integrates with IoT, data analytics, and cloud computing in Industry 4.0. In this context, Table 3 presents an overview of the diverse processes and algorithms employed in manufacturing. The table serves as a valuable reference for the discussion on the utilization of ML and AI in manufacturing, as demonstrated in the following examples.

Computer-based monitoring is an important aspect of Industry 4.0 that includes both ML and AL. The latest sensors, such as RGB detection camaras equipped with ML, have proven efficient and effective in monitoring with higher output for inspection. Computer vision gathers data in the form of videos and images fed to ML for analysis and optimization, enabling a process to continuously monitor the smart manufacturing. Chen *et al.*[24] analyzed and implemented a data-driven system to detect wire bonding defects in the manufacturing of integrated circuits (ICs). The method used data processing to separate and locate defects in images of ICs. Data were gathered through X-ray imaging from the assembly line. ML algorithms such as SVM (Support Vector Machine), VDS (Velocity Distance Support), and CNN (Convolutional Neural Network) were employed to develop the modern monitoring and inspection system for ICs fabrication. SVM was found to be the most useful of the algorithms in terms of fault detection. Zhang and Gao[25] employed an ML-based detection system for optimization of reagent for floatation during extraction of iron ore. During the extraction of minerals, especially iron, workers must constantly adjust the dose of reagent; the quality of the final extracted mineral is dependent on the dosage. ML algorithms were developed using neural networks. A database was built using images of flotation tailings to differentiate the grade of iron ore. After using more than 13 artificial neural networks, an optimized ML-based system was developed that had 97% accuracy in detection variations.

Table 3. Application of various processes and algorithms in manufacturing.

Process	Application	AI Algorithms	References
Process planning for a manufacturing unit	Scheduling, cost planning, energy analysis, process modeling, and optimization	Decision trees, Q-learning, RF, GBT, ANN, SVR	[22,26–28]
Quality assurance and control	Quality improvement, cost optimization, process optimization	Decision trees, SVM, ANN, RF	[29–33]
Maintenance and failure prediction	Smooth operations and processes	KNN, PCA, ANN	[34–37]
Logistics and supply chain	Assigning tasks and scheduling	Q-learning, RF, ANN, deep learning	[38–41]
Robotics in manufacturing	Integrating robotic systems, autonomous processes, robot–human collaboration	Markov model, ANN, deep learning, and networks	[42–45]
Learning and assistance process systems	Recognition of process variations and different objects	ANN, ML	[46]
Control and process parameter optimization	Optimization of process parameters and process forecasting	GBT, ANN, SVM, decision trees	[47–51]

3.3 Process control and fault detection

The efficiency of smart manufacturing improves with advanced fault detection systems that aid in process sustainability. Modern tools combined with ML algorithms help in achieving a strategic edge over competitors. The use of high-end manufacturing fault detection systems not only improves the production time but also ensures high-quality products for end users. Wang *et al*.[52] explained and analyzed a method based on CNN-DLSTM learning to detect faults in the manufacturing of rolling bearings. The fault diagnostic system was based on deep long short-term memory (DLSTM) and convolutional neural networks (CNN). The study primarily focused on the faults in bearings for different working conditions in which gathering large-scale data proved difficult. Deformable CNN enhanced the ability of standard CNNs for local feature extraction using fixed geometric structures. DLSTM further encoded the sequential information contained in the output of deformable CNN. Dense layers were applied to capture high-level features and then classify them into data samples for different fault types. Approaches such as transfer learning were used to feed data for pre-training a fault detection mechanism using sample data from various working conditions. The model could then be used to optimize other conditions and processes. The developed framework, combined with real-time data, exhibited better output efficiency and results. Additionally, Glaser *et al*.[53] studied the vibrations of various production machine to assess the conditions of machines. Deep learning techniques, such as deep tree (DT) and CNN, were used to study the relationship between machine condition and faults in products. Data on vibrations of machines in cold forging industries were collected. CNN was able to detect faults with 99.6% accuracy, while DT detected faults with 92.5% accuracy without classification.

3.4 Quality assurance

Using ML and AI, quality control can be automated completely. Smart manufacturing and AI can inspect all the final output for quality checks. This can dramatically reduce the number of products reaching end users. Smart monitoring systems can detect color, texture, physical shape, tolerance, and packaging. The intrinsic complexity of modern manufacturing units (comprising machining, production line, and assembly), together with unanticipated interruptions and various uncertainties, make it extremely difficult to ensure product quality in sectors like aerospace and automotives and in modern manufacturing in general. As a result, effective solutions for automating and detecting problems are valuable to manufacturers. These solutions are based on real-time data and AI and ML models. Automated detection and visual inspections—enhanced with deep learning approaches to predict possible defects—are used to prevent issues in manufacturing processes, opening the possibility of zero-fault production models.[54]

3.5 Enhanced security of industries

Industry 4.0 uses many data sets and sources, as well as newer technologies such as cloud computing, IoT, blockchain, and AI, to improve and optimize manufacturing process efficiency. However, this comes at the expense of potential cybersecurity vulnerabilities and threats.

Federated learning techniques, which distribute the training and learning process among industrial manufacturing nodes, have recently emerged as a solution to address stated scalability and privacy difficulties. These nodes have the ability to collaborate by using only local characteristics in development of a model using central learning tools without sharing any sensitive and important private data sets.[55] Although this is a significant improvement in terms of addressing important security and data privacy issues, new studies have pointed out a number of risks associated with federated learning tools, particularly with regard to attacks, such as reverse engineering, that can directly extract important information based on real-time datasets.[56] Future research must focus on privacy aspects of AI and ML models by employing differential privacy and safe multi-party computational techniques.

Smart and modern manufacturing industries are using integrated communication frameworks to share real-time data for processing units. The communication is based on network connectivity through the internet. This massive movement of data requires state-of-the-art security protocols and end-to-end data encryption to avoid data misuse and attack. Every networking node must be protected by designing the smart manufacturing unit with integrated security systems in place.[57]

3.6 Data analytics

The goal of smart manufacturing is to translate and transform real-time data analytics into efficient output for intelligent manufacturing processes. Modern industries have more than 100 EB data gathered annually from manufacturing processes. Big Data analytics can be used in optimizing and maximizing process efficiency through timely decisions.[58] In short, Big Data is a necessary part of smart manufacturing and Industry 4.0. Manufacturers have started to realize that this enormous amount of data holds great strategic value, dependent not merely on the collection of the data but the underlying knowledge base that can be proven very effective. Dubay *et al*.[59] explained the worldwide manufacturing practices and use of AI and Big Data analytics for sustainable growth. The integration of IoT, Big Data and smart manufacturing units has enabled the exploitation of the data to the fullest. The study briefly explained the relationship between Big Data and smart manufacturing, arguing that the lack of implementation of research studies to industrial manufacturing has resulted in a huge gap in defining the effective role of data analytics. Research on Big Data concentrates on value addition, but there are other factors of considerable relevance to smart manufacturing, including velocity, volume, and variety. Studies by Brown *et al*.[60] stressed the importance of Big Data analytics for manufacturing planning, business decision-making, sustainability, environmental implications, supply chain, human resources, and lean manufacturing. Smart manufacturing and Industry 4.0 are dependent on customer satisfaction using Big Data analytics for enhanced efficiency, speed, cost, and quality. Ultimately, Big Data analytics boost the user experience through constant process innovation and timely business decision-making.

Big Data involves multi-source product data gathered from the life cycle analysis in manufacturing. The data are considered based on quantity (volume), variety (diverse heterogeneous data sources), velocity (high-speed data gathering), veracity (diverse uncomplete data with errors, approximations, and inconsistency), and value addition (the outcome of data analytics). Big Data from manufacturing can be divided into management data, user data, product data, and public data.[61] Management data can be collected through smart manufacturing systems, and data analytics aids in planning, management, maintenance, job assigning, sales, marketing, and inventory management. The management data analytics can further be extended to customer service as well as financial management of the manufacturing units. The equipment data is used to optimize the processes and monitor process parameters to assess real-time performance. Different internet sources and public data can strengthen the supply chain for different demographics and meet the supply and needs of end users. Large industries use efficient and cost-effective data collection and processing systems, such as IoT and data computing, to digitize manufacturing capabilities.

3.6.1 Data collection

The data collection process in the manufacturing industry takes a variety of forms, such as IoT, smart sensors, and intelligent systems. In industrial manufacturing units and products, for example, built-in integrated sensors enable continuous measurement, monitoring, and reporting of real-time operational parameters like pressure, temperature, and vibrations. RFID is used in identification, management of numerous workpieces, tracking, and raw material inventory management for production. Additionally, the development of internet connectivity opens the door to collecting user data via smart terminals such as PCs, mobile phones, tablets, and laptops. Data can also be gathered using software development kits and other programming interfaces. Additionally, web crawling is a popular data acquisition method to gather public data based on specific criteria and boundaries established by engineers and AI. Web crawling is the process of using "crawler" programs to search publicly accessible web pages and information to gather useful data.

3.6.2 Data storage

The massive amount of data gathered within manufacturing operations needs successful integrating and secure storage. Manufacturing data comprises three categories: structured data, *e.g.*, numbers and tables; semi-structured data, *e.g.*, graphs, trees, and XML documents; and unstructured data, *e.g.*, log books, audio files, videos, and imaging. The management of unstructured data in corporate databases is challenging, which is why industrial manufacturers have always placed a strong emphasis on storing structured data. Cloud computing provides cost-effective and efficient data storage solutions.

3.6.3 Data processing

Data processing is a term for operations used to extract information from a massive chunk of data. Data visualization aids manufacturers in making calculated, informed, and logical decisions. Data must be pre-processed systematically to eliminate redundant, identical, false, and inconsistent information. Data sorting and cleaning includes the following tasks: missing values, improper format, duplication, and junk data cleaning. The latest data reduction processing can organize and simplify the enormous volume of data. ML and AI can be applied to process filtered data. Data analytics employs computing resources, various forecasting models, data crunching techniques, and predictions to present insights and forecasting of manufacturing unit performance.

3.6.4 Data-driven smart manufacturing

Optimization of manufacturing is dependent on the exploitation of Big Data. Data analytics through AI and ML have shifted the paradigm toward smart manufacturing. Big Data analytics is employed to process, store, and gather real-time data. As Tao *et al*.[61] explained, the data-based smart manufacturing framework is divided into four unit types: manufacturing, data, monitoring, and processing. Manufacturing units may be autonomous and perform various manufacturing activities, including input and output of products, collection of data, and monitoring of human interactions. Data units are related to collecting manufacturing data that is fed through cloud computing. The data are thoroughly analyzed for actionable decisions and outcomes. Data analytics is employed in planning, designing, and manufacturing to enhance process efficiency. Monitoring units get the manufacturing data in real time for the development of optimal and sustainable process strategies. Processing units are designed for the swift processing of massive amounts of data to predict issues, diagnose problems, and recommend effective solutions.

3.6.5 Tuning AI and ML models for manufacturing

Once an AI or ML model has been trained, it is important to tune the model to improve its performance on manufacturing data. Tuning can be done by adjusting the hyperparameters of the model. Hyperparameters are parameters that are not learned from the data but are instead set by the user.

There are a variety of hyperparameters that can be tuned in AI and ML models. Some common hyperparameters include the following:

- ❖ **Learning rate:** The learning rate controls how quickly the model updates its parameters during training.
- ❖ **Number of epochs**: The number of epochs is the number of times the model will iterate over the training data.
- ❖ **Batch size:** The batch size is the number of training examples that are used to update the model's parameters at each iteration.
- ❖ **Regularization parameters:** Regularization parameters are used to prevent the model from overfitting the training data.

The optimal hyperparameters for a given model will vary depending on the specific manufacturing data that is being used. It is important to experiment with different hyperparameters to find the set of hyperparameters that results in the best model performance.

Here are some specific examples of how tuning can be used to improve the performance of AI and ML models in manufacturing:

- ❖ **Tuning a predictive maintenance model:** A predictive maintenance model can be tuned to improve its accuracy at predicting when machines are likely to fail. This can be done by adjusting the hyperparameters of the model, such as the learning rate and the number of epochs.
- ❖ **Tuning a quality control model:** A quality control model can be tuned to improve its accuracy at detecting defects in products. This can be done by adjusting the hyperparameters of the model, such as the batch size and the regularization parameters.
- ❖ **Tuning a production optimization model:** A production optimization model can be tuned to improve its accuracy at predicting the optimal production schedule. This can be done by adjusting the hyperparameters of the model, such as the learning rate and the number of epochs.

Tuning is an important part of the process of developing and deploying AI and ML models in manufacturing. By carefully tuning the hyperparameters of a model, manufacturers can improve the performance of the model and achieve better results.

4. Limitations and prospects of AI and ML

Most manufacturing systems carry out multiple operations following predetermined production logic and plans utilizing conventional process machines. To support these machines, manual and paper-based working methods are frequently employed. Under this method, there are several difficulties. First, low working efficiency is caused by the lengthy procedures, executions, and interactions that take place on shop floors when many people are involved. For instance, whenever there are re-engineered designs, the technicians, machine operators, chief engineers, and floor supervisors typically gather to propose a solution. It is extremely normal for these meetings to take four hours or longer, as all parties must first share information or related data to assess the present situation to find a workable solution. Second, paper data sheets or record books are typically used for data collection. The WIP level, working components, and other crucial information must be recorded by various personnel. Workers are often preoccupied with running equipment and dislike spending time entering data for non-value-added operations. Third, shop floor supervisors must utilize data to make decisions about scheduling and planning production. Unfortunately, most decisions are based on information and data from paper sheets or record books, and these decisions are often irrational and impractical. This is because managing a large number of paper sheets and cards, where the information collected is constantly delayed, takes a great deal of time and work.[62] For most industrial organizations, real-time data collection is necessary to progress with Industry 4.0. IoT and CPS may present a solution.

4.1 Trust in AI and ML

Trust features extensively in a wide range of social scientific topics. There are different definitions and analytical frameworks used to examine the trust factor. Although trust is frequently and naturally used in speech and everyday work, it remains difficult to explain and define the concept. Andras *et al*. explained how trust is treated across several disciplines and professions:

"In the social world trust is about the expectation of cooperative, supportive, and non-hostile behavior. In psychological terms, trust is the result of cognitive learning from experiences of trusting behavior with others. Philosophically, trust is the taking of risk based on a moral relationship between individuals. In the context of economics and international relations, trust is based on calculated incentives for alternative behaviors, conceptualized through game theory.[63]

Mayer *et al*.[64] identified three main aspects of trust: Benevolence, Ability, and Integrity. Similarly, Dietz and Hortog[65] discussed different forms and types of trust, *i.e.*, belief, decision, and respective actions. This study emphasized the importance of these three crucial forms of trust to get useful results out of the system. As concerns the latest technologies and systems, the main issues requiring trust are the handling of vast amounts of data, safeguarding privacy, and preventing data misuse. A trusted and secure cybersecurity setup, as illustrated in Fig. 3, goes a long way in establishing user trust.

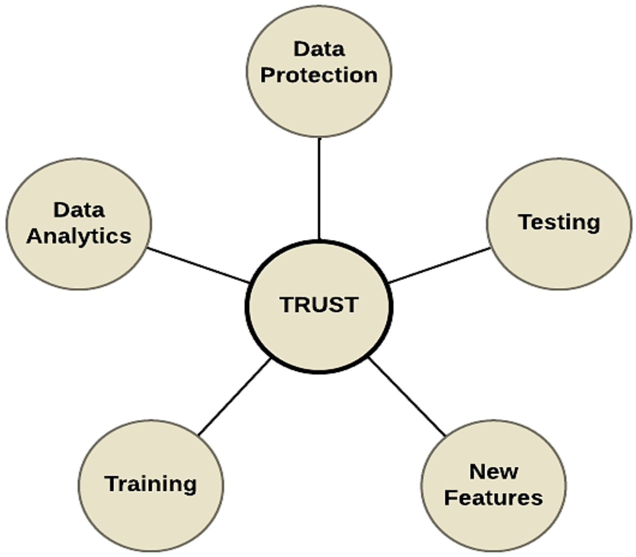

Fig. 3 Lifecycle of trust for AI and ML.

5. Discussion

The discussion section provides a comprehensive and insightful analysis of the topic, and it highlights the importance of AI and ML in manufacturing. The section also discusses the challenges and opportunities associated with these technologies, and it provides the future prospectives to get involved in developing and implementing AI and ML in manufacturing.

5.1 AI and ML in smart manufacturing

AI and ML are rapidly transforming the manufacturing industry. These technologies are being used to automate tasks, improve efficiency, and optimize processes. AI and ML-powered systems can collect and analyze data from a variety of sources, including sensors, machines, and people. This data can then be used to make better decisions about manufacturing operations.

One of the key benefits of AI and ML in manufacturing is that it can help to automate tasks that are currently done by humans. This can free up workers to focus on more value-added activities. For example, AI and ML can be used to automate tasks such as quality control, predictive maintenance, and supply chain management.

AI and ML can also help to improve manufacturing efficiency. For example, AI-powered systems can be used to optimize production schedules, reduce waste, and improve product quality. AI and ML can also be used to develop new manufacturing processes that are more efficient and sustainable.

5.2 Challenges and opportunities

While AI and ML offer significant potential benefits for manufacturing, there are also some challenges that need to be addressed. One challenge is the need to develop new data storage and processing solutions that can handle the massive amounts of data generated by manufacturing processes.

Another challenge is the need to develop AI and ML systems that are reliable and secure. Manufacturers need to be confident that these systems will not make mistakes or be susceptible to cyberattacks.

Despite these challenges, the opportunities offered by AI and ML in manufacturing are significant. AI and ML have the potential to revolutionize the manufacturing industry by making it more efficient, productive, and sustainable.

5.3 Future of AI and ML in manufacturing

The future of AI and ML in manufacturing is very promising. As these technologies continue to develop and mature, they will become even more powerful and versatile. This will lead to new and innovative applications of AI and ML in manufacturing. For example, AI and ML could be used to develop self-optimizing manufacturing systems that can learn and adapt to changing conditions. These systems could be used to produce products that are customized to individual needs and preferences. AI and ML could also be used to develop new manufacturing processes that are more sustainable and environmentally friendly. For example, AI and ML could be used to optimize energy consumption and reduce waste. Overall, the future of AI and ML in manufacturing is very bright. These technologies have the potential to transform the manufacturing industry and make it more efficient, productive, and sustainable.

5.4 Role of government and industry

Government and industry can play a key role in supporting the development and adoption of AI and ML in manufacturing. Governments can provide funding for research and development, and they can also develop policies that encourage the adoption of these technologies. Industry can also play a role by investing in AI and ML research and development, and by working with government to develop policies that support the adoption of these technologies.

6. Conclusion

This review tracks the changes and implementation of AI and ML–based algorithms at an industrial scale. The study highlights the primary Industrial AI trends in research and implementation of modern technologies and application domains for AI based on real-time data analytics. It recognizes, identifies, and explains the fundamental designing principles that play a role in the integration of AI into various applications. These principles have an impact on the development, application, and implementation of next-generation Industrial AI systems, particularly for the manufacturing sector. To reach the stated goals, this detailed review examined the capabilities of these modern systems, determining that the working of smart manufacturing units is based on smart process design, monitoring, control, scheduling, and industrial applications. Techniques related to CPS, IoS, Big Data and analytics, and advanced robotics are incorporated into smart manufacturing. These technologies are transforming the world through intelligent manufacturing, also known as smart manufacturing. The combined effect of real-time data, human factors, smart AI algorithms, and data analytics enhances manufacturing capabilities. Modern AI and ML–based manufacturing systems have brought about a revolution within industries by integrated tools such as smart monitoring, fault detection, and smart controls.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

References

[1] J. McCarthy, M. L. Minsky, N. Rochester, C.E. Shannon, A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955, AI magazine, 2006, **27**, 12, doi: 10.1609/aimag.v27i4.1904.

[2] R. Cioffi, M. Travaglioni, G. Piscitelli, A. Petrillo, F. De Felice, Artificial intelligence and machine learning applications in smart production: progress, trends, and directions, *Sustainability*, 2020, **12**, 492, doi: 10.3390/su12020492.

[3] R. Y. Zhong, X. Xu, E. Klotz, S. T. Newman, Intelligent manufacturing in the context of industry 4.0: a review, *Engineering*, 2017, **3**, 616-630, doi: 10.1016/j.eng.2017.05.015.

[4] B.-H. Li, B.-C. Hou, W.-T. Yu, X.-B. Lu, C.-W. Yang, Applications of artificial intelligence in intelligent manufacturing: a review, *Frontiers of Information Technology & Electronic Engineering*, 2017, **18**, 86-96, doi: 10.1631/FITEE.1601885.

[5] A. Lasi, P. Fettke, H. Kemper, T. Mehner, M. Winkler, Industry 4.0 and the industrial internet of things (IIoT): An overview, *Procedia Manufacturing*, 2019, **3**, 17-23, doi: 10.1016/j.procs.2019.01.001.
[6] I. Ahmed, G. Jeon, F. Piccialli, From artificial intelligence to explainable artificial intelligence in industry 4.0: a survey on what, how, and where, *IEEE Transactions on Industrial Informatics*, 2022, **18**, 5031-5042, doi: 10.1109/TII.2022.3146552.
[7] M. Abu-Elkheir, M. Hayajneh, N. A. Ali, Data management for the Internet of Things: design primitives and solution, *Sensors*, 2013, **13**, 15582-15612, doi: 10.3390/s131115582.
[8] B. Kolarevic, Architecture in the Digital Age: Design and Manufacturing, Taylor & Francis, 2004.
[9] L. P. Berg, J. M. Vance, Industry use of virtual reality in product design and manufacturing: a survey, *Virtual Reality*, 2017, **21**, 1-17, doi: 10.1007/s10055-016-0293-9.
[10] P. Fraga-Lamas, T. M. FernáNdez-CaraméS, Ó. Blanco-Novoa, M. A. Vilar-Montesinos, A review on industrial augmented reality systems for the industry 4.0 shipyard, *IEEE Access*, 2018, **6**, 13358-13375, doi: 10.1109/ACCESS.2018.2808326.
[11] H.-S. Park, N.-H. Tran, Development of a smart machining system using self-optimizing control, *The International Journal of Advanced Manufacturing Technology*, 2014, **74**, 1365-1380, doi: 10.1007/s00170-014-6076-0.
[12] X. Qiu, H. Luo, G. Xu, R. Zhong, G. Q. Huang, Physical assets and service sharing for IoT-enabled Supply Hub in Industrial Park (SHIP), *International Journal of Production Economics*, 2015, **159**, 4-15, doi: 10.1016/j.ijpe.2014.09.001.
[13] C. Zhang, J. Yang, A History of Mechanical Engineering, Springer, 2020.
[14] H. Mohajan, The Second Industrial Revolution Has Brought Modern Social and Economic Developments, 2019. https://mpra.ub.uni-muenchen.de/id/eprint/9820.
[15] A. Petrillo, F. De Felice, R. Cioffi, F. Zomparelli, Fourth industrial revolution: current practices, challenges, and opportunities. A. Petrillo, R. Cioffi, F. De Felice, eds. Digital Transformation in Smart Manufacturing. InTech, 2018, 1-20, doi: 10.5772/intechopen.72304.
[16] N. Carvalho, O. Chaim, E. Cazarini, M. Gerolamo, Manufacturing in the fourth industrial revolution: a positive prospect in Sustainable Manufacturing, *Procedia Manufacturing*, 2018, **21**, 671-678, doi: 10.1016/j.promfg.2018.02.170.
[17] S. Fahle, C. Prinz, B. Kuhlenkötter, Systematic review on machine learning (ML) methods for manufacturing processes–Identifying artificial intelligence (AI) methods for field application, *Procedia CIRP*, 2020, **93**, 413-418, doi: 10.1016/j.procir.2020.04.109.
[18] G. Ø. Rønsch, M. Kulahci, M. Dybdahl, An investigation of the utilisation of different data sources in manufacturing with application in injection moulding, *International Journal of Production Research*, 2021, **59**, 4851-4868, doi: 10.1080/00207543.2021.1893853.
[19] R. Lorenz, J. Senoner, W. Sihn, T. Netland, Using process mining to improve productivity in make-to-stock manufacturing, *International Journal of Production Research*, 2021, **59**, 4869-4880, doi: 10.1080/00207543.2021.1906460.
[20] F. Zangaro, S. Minner, D. Battini, A supervised machine learning approach for the optimisation of the assembly line feeding mode selection, *International Journal of Production Research*, 2021, **59**, 4881-4902, doi: 10.1080/00207543.2020.1851793.
[21] R. Rentsch, C. Heinzel, E. Brinksmeier, Artificial intelligence for an energy and resource efficient manufacturing chain design and operation, *Procedia CIRP*, 2015, **33**, 139-144, doi: 10.1016/j.procir.2015.06.026.
[22] B. Brik, B. Bettayeb, M. Sahnoun, F. Duval, Towards predicting system disruption in industry 4.0: machine learning-based approach, *Procedia Computer Science*, 2019, **151**, 667-674, doi: 10.1016/j.procs.2019.04.089.
[23] J. Walther, D. Spanier, N. Panten, E. Abele, Very short-term load forecasting on factory level–A machine learning approach, *Procedia CIRP*, 2019, **80**, 705-710, doi: 10.1016/j.procir.2019.01.060.
[24] J. Chen, Z. Zhang, F. Wu, A data-driven method for enhancing the image-based automatic inspection of IC wire bonding defects, *International Journal of Production Research*, 2021, **59**, 4779-4793, doi: 10.1080/00207543.2020.1821928.
[25] D. Zhang, X. Gao, Soft sensor of flotation froth grade classification based on hybrid deep neural network, *International Journal of Production Research*, 2021, **59**, 4794-4810, doi: 10.1080/00207543.2021.1894366.
[26] D. Kim, T. Lee, S. Kim, B. Lee, H. Y. Youn, Adaptive packet scheduling in IoT environment based on Q-learning, *Journal of Ambient Intelligence and Humanized Computing*, 2020, **11**, 2225-2235, doi: 10.1007/s12652-019-01351-w.
[27] M. Lubosch, M. Kunath, H. Winkler, Industrial scheduling with Monte Carlo tree search and machine learning, *Procedia CIRP*, 2018, **72**, 1283-1287, doi: 10.1016/j.procir.2018.03.171.
[28] J.-L. Loyer, E. Henriques, M. Fontul, S. Wiseall, Comparison of Machine Learning methods applied to the estimation of manufacturing cost of jet engine components, *International Journal of Production Economics*, 2016, **178**, 109-119, doi: 10.1016/j.ijpe.2016.05.006.
[29] J. Huber, C. Tammer, S. Krotil, S. Waidmann, X. Hao, C. Seidel, G. Reinhart, Method for classification of battery separator defects using optical inspection, *Procedia CIRP*, 2016, **57**, 585-590, doi: 10.1016/j.procir.2016.11.101.
[30] B. Staar, M. Lütjen, M. Freitag, Anomaly detection with convolutional neural networks for industrial surface inspection, *Procedia CIRP*, 2019, **79**, 484-489, doi: 10.1016/j.procir.2019.02.123.
[31] A. Lokrantz, E. Gustavsson, M. Jirstrand, Root cause analysis of failures and quality deviations in manufacturing using machine learning, *Procedia CIRP*, 2018, **72**, 1057-1062, doi: 10.1016/j.procir.2018.03.229.
[32] S. Pachner, J. Miethlinger, Smart data analysis for optimized manufacturing of powder coatings on co-rotating twin screw

extrudersAIP Conference Proceedings. Dresden, Germany. Author(s), 2019, doi: 10.1063/1.508454.
[33] V. Hirsch, P. Reimann, O. Kirn, B. Mitschang, Analytical approach to support fault diagnosis and quality control in end-of-line testing, *Procedia CIRP*, 2018, **72**, 1333-1338, doi: 10.1016/j.procir.2018.03.024.
[34] R. Pinto, T. Cerquitelli, Robot fault detection and remaining life estimation for predictive maintenance, *Procedia Computer Science*, 2019, **151**, 709-716, doi: 10.1016/j.procs.2019.04.094.
[35] M. Kraus, S. Feuerriegel, Forecasting remaining useful life: Interpretable deep learning approach via variational Bayesian inferences, *Decision Support Systems*, 2019, **125**, 113100, doi: 10.1016/j.dss.2019.113100.
[36] G. Scalabrini Sampaio, A. R. A. Vallim Filho, L. Santos da Silva, L. Augusto da Silva, Prediction of motor failure time using an artificial neural network, *Sensors*, 2019, **19**, 4342, doi: 10.3390/s19194342.
[37] K. Prabu and V. Chahal, Predict Equipment Failure Using IoT Sensor Data, Armonk, NY: IBM, 2018. Available: https://developer.ibm.com/patterns/predict-equipment-failure-usingiot-sensor-data.
[38] A. Kuhnle, L. Schäfer, N. Stricker, G. Lanza, Design, implementation and evaluation of reinforcement learning for an adaptive order dispatching in job shop manufacturing systems, *Procedia CIRP*, 2019, **81**, 234-239, doi: 10.1016/j.procir.2019.03.041.
[39] Y.-R. Shiue, K.-C. Lee, C.-T. Su, Real-time scheduling for a smart factory using a reinforcement learning approach, *Computers and Industrial Engineering*, 2018, **125**, 604-614, doi: 10.1016/j.cie.2018.03.039.
[40] B. Waschneck, A. Reichstaller, L. Belzner, T. Altenmüller, T. Bauernhansl, A. Knapp, A. Kyek, Optimization of global production scheduling with deep reinforcement learning, *Procedia CIRP*, 2018, **72**, 1264-1269, doi: 10.1016/j.procir.2018.03.212.
[41] D. Knoll, D. Neumeier, M. Prüglmeier, G. Reinhart, An automated packaging planning approach using machine learning, *Procedia CIRP*, 2019, **81**, 576-581, doi: 10.1016/j.procir.2019.03.158.
[42] X. Chen, J. Guhl, Industrial Robot Control with Object Recognition based on Deep Learning, *Procedia CIRP*, 2018, **76**, 149-154, doi: 10.1016/j.procir.2018.01.021.
[43] D. Kuhner, L. D.J. Fiederer, J. Aldinger, F. Burget, M. Völker, R. T. Schirrmeister, C. Do, J. Boedecker, B. Nebel, T. Ball, W. Burgard, A service assistant combining autonomous robotics, flexible goal formulation, and deep-learning-based brain–computer interfacing, *Robotics and Autonomous Systems*, 2019, **116**, 98-113, doi: 10.1016/j.robot.2019.02.015.
[44] Y. Tsurumine, Y. Cui, E. Uchibe, T. Matsubara, Deep reinforcement learning with smooth policy update: application to robotic cloth manipulation, *Robotics and Autonomous Systems*, 2019, **112**, 72-83, doi: 10.1016/j.robot.2018.11.004.
[45] S. Yin, W. Ji, L. Wang, A machine learning based energy efficient trajectory planning approach for industrial robots, *Procedia CIRP*, 2019, **81**, 429-434, doi: 10.1016/j.procir.2019.03.074.
[46] M. Haslgrübler, B. Gollan, A. Ferscha, A cognitive assistance framework for supporting human workers in industrial tasks, *IT Professional*, 2018, **20**, 48-56, doi: 10.1109/MITP.2018.053891337.
[47] A. du Preez, G. A. Oosthuizen, Machine learning in cutting processes as enabler for smart sustainable manufacturing, *Procedia Manufacturing*, 2019, **33**, 810-817, doi: 10.1016/j.promfg.2019.04.102.
[48] S. Hwang, G. Jeon, J. Jeong, J. Lee, A Novel Time Series based Seq2Seq Model for Temperature Prediction in Firing Furnace Process, *Procedia Computer Science*, 2019, **155**, 19-26, doi: 10.1016/j.procs.2019.08.007.
[49] P. Vazan, D. Janikova, P. Tanuska, M. Kebisek, Z. Cervenanska, Using data mining methods for manufacturing process control, *IFAC-PapersOnLine*, 2017, **50**, 6178-6183, doi: 10.1016/j.ifacol.2017.08.986.
[50] T. Küfner, T. H.-J. Uhlemann, B. Ziegler, Lean data in manufacturing systems: using artificial intelligence for decentralized data reduction and information extraction, *Procedia CIRP*, 2018, **72**, 219-224, doi: 10.1016/j.procir.2018.03.125.
[51] J. Sossenheimer, J. Walther, J. Fleddermann, E. Abele, A sensor reduced machine learning approach for condition-based energy monitoring for machine tools, *Procedia CIRP*, 2019, **81**, 570-575, doi: 10.1016/j.procir.2019.03.157.
[52] Z. Wang, Q. Liu, H. Chen, X. Chu, A deformable CNN-DLSTM based transfer learning method for fault diagnosis of rolling bearing under multiple working conditions, *International Journal of Production Research*, 2021, **59**, 4811-4825, doi: 10.1080/00207543.2020.1808261.
[53] A. Glaeser, V. Selvaraj, S. Lee, Y. Hwang, K. Lee, N. Lee, S. Lee, S. Min, Applications of deep learning for fault detection in industrial cold forging, *International Journal of Production Research*, 2021, **59**, 4826-4835, doi: 10.1080/00207543.2021.1891318.
[54] R. S. Peres, J. Barata, P. Leitao, G. Garcia, Multistage quality control using machine learning in the automotive industry, *IEEE Access*, 1871, **7**, 79908-79916, doi: 10.1109/ACCESS.2019.2923405.
[55] R. S. Peres, X. Jia, J. Lee, K. Sun, A. W. Colombo, J. Barata, Industrial artificial intelligence in industry 4.0 - systematic review, challenges and outlook, *IEEE Access*, 2874, **8**, 220121-220139, doi: 10.1109/ACCESS.2020.3042874.
[56] G. Xu, H. Li, S. Liu, K. Yang, X. Lin, VerifyNet: secure and verifiable federated learning, *IEEE Transactions on Information Forensics and Security*, 2019, **15**, 911-926, doi: 10.1109/TIFS.2019.2929409.
[57] K.-D. Thoben, S. Wiesner, T. Wuest, “industrie 4.0” and smart manufacturing–A review of research issues and application examples, *International Journal of Automation Technology*, 2017, **11**, 4-16, doi: 10.20965/ijat.2017.p0004.

[58] S. Yin, O. Kaynak, Big data for modern industry: challenges and trends, *Proceedings of the IEEE*, 2015, **103**, 143-146, doi: 10.1109/JPROC.2015.2388958.
[59] R. Dubey, A. Gunasekaran, S. J. Childe, S. F. Wamba, T. Papadopoulos, The impact of big data on world-class sustainable manufacturing, *The International Journal of Advanced Manufacturing Technology*, 2016, **84**, 631-645, doi: 10.1007/s00170-015-7674-1.
[60] S. Brown, B. Squire, K. Blackmon, The contribution of manufacturing strategy involvement and alignment to world-class manufacturing performance, *International Journal of Operations & Production Management*, 2007, **27**, 282-302, doi: 10.1108/01443570710725554.
[61] F. Tao, Q. Qi, A. Liu, A. Kusiak, Data-driven smart manufacturing, *Journal of Manufacturing Systems*, 2018, **48**, 157-169, doi: 10.1016/j.jmsy.2018.01.006.
[62] P. Zheng, H. wang, Z. Sang, R. Y. Zhong, Y. Liu, C. Liu, K. Mubarok, S. Yu, X. Xu, Smart manufacturing systems for Industry 4.0: conceptual framework, scenarios, and future perspectives, *Frontiers of Mechanical Engineering*, 2018, **13**, 137-150, doi: 10.1007/s11465-018-0499-5.
[63] P. Andras, L. Esterle, M. Guckert, T. A. Han, P. R. Lewis, K. Milanovic, T. Payne, C. Perret, J. Pitt, S. T. Powers, N. Urquhart, S. Wells, Trusting intelligent machines: deepening trust within socio-technical systems, *IEEE Technology and Society Magazine*, 2018, **37**, 76-83, doi: 10.1109/mts.2018.2876107.
[64] R. C. Mayer, J. H. Davis, F. D. Schoorman, An integrative model of organizational trust, *The Academy of Management Review*, 1995, **20**, 709-734, doi: 10.2307/258792.
[65] G. Dietz, D. N. Den Hartog, Measuring trust inside organisations, *Personnel Review*, 2006, **35**, 557-588, doi: 10.1108/00483480610682299.

Publisher's Note: Engineered Science Publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

