Chapter 8
Smart Manufacturing

Paul D. Clough and Jon Stammers

Abstract The ability to connect a growing range of technologies, such as sensors, Internet of (Industrial) Things, cloud computing, Big Data analytics, AI, mobile devices, and augmented/virtual reality, is helping to take manufacturing to new levels of "smartness." Such technologies have the opportunity to transform, automate, and bring intelligence to manufacturing processes and support the next manufacturing era. In this chapter, we describe the manufacturing context; emerging concepts, such as Industry 4.0; and technologies that are driving change and innovation within the manufacturing industry.

Keywords Industry 4.0 · Smart manufacturing · IoT · Industrial IoT · AI

Key Points

- Review of the key technologies being used to support smart manufacturing, such as AI, Industrial IoT, cloud computing, and augmented/virtual reality
- Content broken down into the following sections: from sensors and connectivity (e.g., Industrial IoT), through developing business value with data (e.g., Big Data analytics and AI), to applications beyond the physical world (e.g., simulation and digital twins)
- Inclusion of several real-life examples and use cases showing how smart manufacturing can be used to transform the manufacturing process
- Discussion of manufacturing applications that go beyond the physical world, including simulation, digital twins, and extending reality
- Summary of the benefits and challenges of smart technology in manufacturing, including change management, integration, security, and lack of skills

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8.1 Introduction to Smart Manufacturing

New technologies, such as AI and Industrial Internet of Things, and the ability to connect them, the availability of vast amounts of data, the maturity of analytics and intelligent systems, and advanced manufacturing techniques are bringing about "smart" manufacturing systems (SMSs) and a new data-driven era for manufacturing (Li et al., 2017; Zheng et al., 2018; Qu et al., 2019). In fact, access to new forms of data and technologies is enabling a convergence between the physical and cyber/digital worlds (Tao et al., 2018). This has manifest itself in the manufacturing strategy of countries with the introduction of new notions of manufacturing, such as Manufacturing Innovation 3.0 in Korea, Made in China 2025, Industry 4.0 in Germany, and Smart Manufacturing in the USA.

8.1.1 The Manufacturing Process

Manufacturing is a well-established industry that turns raw materials into products through a series of processes and activities, such as product design, acquiring of raw materials, and the processing of materials (Dahotre & Harimkar, 2008). Many manufacturing processes exist; however, the industry is facing continuous changes—new technologies, new processes, and new consumer demands—making manufacturing increasingly more complex and dynamic. Figure 8.1 illustrates a typical manufacturing process—multistage manufacture of a high-value component (e.g., the fabrication of metal components and assembling them into parts), covering the journey from raw material from the supplier, through design, to the shipping of an assembly (Bralla, 2007).

In the example in Fig. 8.1, the component undergoes multiple machining processes using computer numerical control (CNC) machinery where pre-programmed software and code control the movement of production equipment. In addition, various inspection and testing stages are undergone using coordinate measuring machine (CMM), a device that measures geometry of physical objects by sensing discrete points on the surface of an object with a probe, as well as final assembly. These stages—4 through to 16—can be considered the *core* manufacturing processes where smart technology could have an impact. However, the stages outside of this can also play a role in enabling smart manufacturing, such as product design and supply chain management, and offer data capture opportunities which can influence the manufacturing processes itself. In the remainder of this chapter, we summarize technologies involved in smart manufacturing that could transform stages of the process in Fig. 8.1.

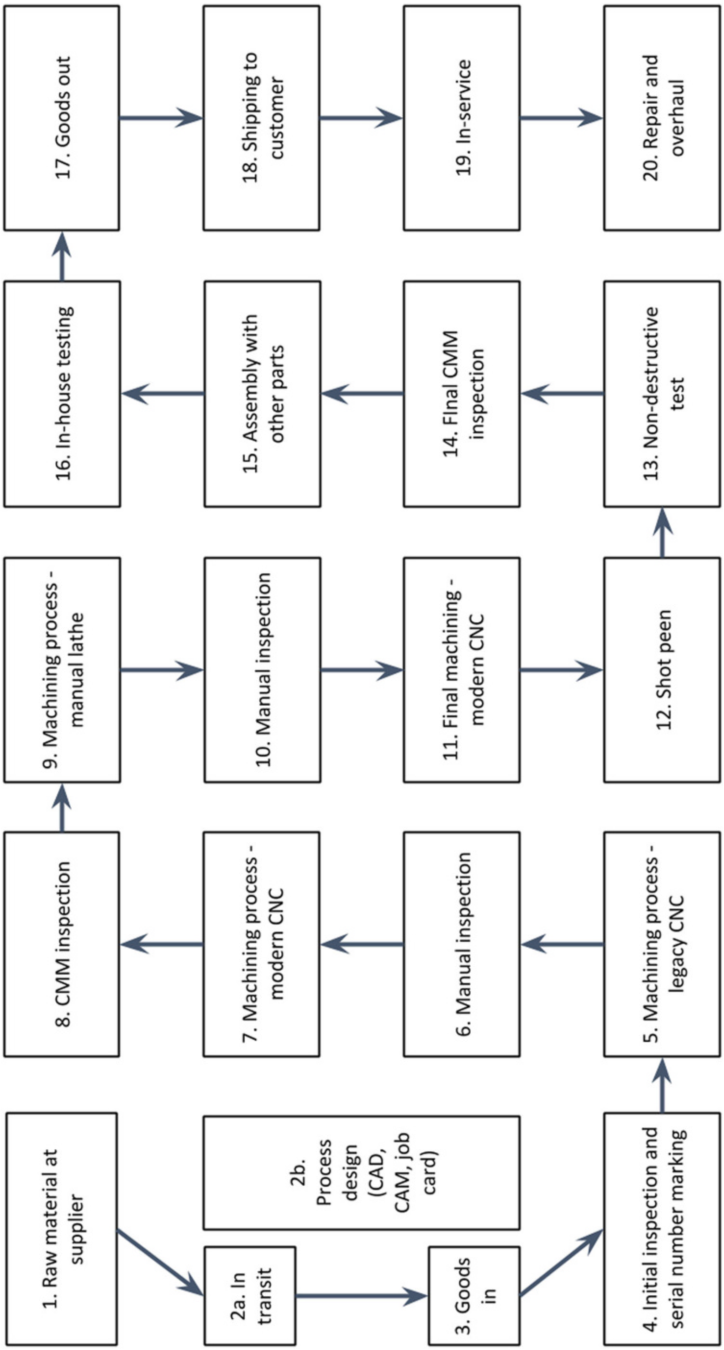

Fig. 8.1 A sample manufacturing process, including product life before and after

8.1.2 Making Manufacturing Smarter

In many ways, manufacturers have often been "smart" by developing or applying new technologies and methods or creating efficient and effective processes to turn raw materials into products, thereby adding value. Indeed, the terms "smart" and "intelligent" were used in earlier industrial eras (Industry 3.0) to describe automation and collaborative manufacturing systems that respond in real time to changing demands and needs. However, the move now is toward data-driven smart manufacturing, whereby wide-scale collection and analysis of vast amounts of (real-time) data at all stages of the manufacturing process is enabling companies to reach new levels of intelligence: "Smart manufacturing, also known as Industry 4.0, refers to the next generation manufacturing paradigm that makes use of smart sensors, cloud computing infrastructures, AI, machine learning, additive manufacturing, and/or advanced robotics to improve manufacturing productivity and cost efficiency" (Wu et al., 2018:1).

In addition to the availability of data, the evolution of smart manufacturing is a combination of technical innovation and emerging technologies, advances in manufacturing, and new manufacturing paradigms (e.g., agile, lean and additive) and automation. This has gone from computer-integrated manufacturing in the 1970s, through intelligent manufacturing in the 1990s, to smart manufacturing systems or SMSs today (Qu et al., 2019; Tao et al., 2018). This is also linked to the fourth industrial revolution and Industry 4.0[1]—the digital transformation of manufacturing/production and related industries and value creation processes (Xu et al., 2018; Alcácer & Cruz-Machado, 2019), which captures the use of data in a connected manufacturing infrastructure (e.g., factory, supply chains, etc.). In the next section, we discuss some of the building blocks for Industry 4.0 and smart manufacturing, including data generation and connectivity using sensors and Industrial IoT (Sect. 8.2), data management and analysis using cloud computing, Big Data and AI (Sect. 8.3), and technologies that take the user beyond the physical world such as simulation, augmented reality, and digital twins (Sect. 8.4).

8.2 The (Industrial) Internet of Things

The term "Internet of Things" (IoT) is now commonplace, referring to devices found in homes, offices, and other environments that contain embedded technology to allow them to sense and interact with their surroundings. When connected to other technology, either directly using local networking or via Internet connectivity, it can lead to intelligent systems (Chu, 2016). Depending on the use of the technology and the intended user, there are three main categories of IoT: (1) *consumer IoT* (e.g., smartphones), (2) *commercial IoT* (e.g., connected medical devices), and

[1] Industry 4.0 itself is also often synonymous with the term "smart industry."

(3) *Industrial IoT*. When applied in industrial systems, IoT technology brings the opportunity to optimize monitoring and control of industrial systems, capturing large amounts of data about those systems, exposing insight previously hidden.

Industrial IoT (IIoT) is a "network of intelligent and highly connected industrial components that are deployed to achieve high production rate with reduced operational costs through real-time monitoring, efficient management and controlling of industrial processes, assets and operational time" (Khan et al., 2020:1). Further enabling technologies include edge computing and analytics, cyber security, cloud computing, wide area networks (4G, 5G, long-range WAN, etc.), wireless networks (WiFi), and data science techniques, such as artificial intelligence and Big Data analytics. Bringing some, or all, of these technologies along with the smart "things" to a production environment can enable smart manufacturing.

A typical IIoT system is illustrated in Fig. 8.2 and highlights a number of typical components found in IIoT scenarios: sensing devices broadcast their measurement results, control devices provide actions as a result of measured data, and devices capture images, either still or video. Importantly, there are multiple assets being monitored, and data from all of these is communicated to the central control center for analysis, insight, and action.

8.2.1 Sensing Technology

A sensor is a device that measures something about its surroundings and sends a signal to an acquisition system. Sensors are a fundamental element of any IoT system (Zheng et al., 2018) and are usually a primary source of data for developing understanding and insight into how a system, or individual asset, is performing. In particular, smart assessment of asset health requires one or more sensing devices. In any sensor application in manufacturing, the typical sequence of events and data flow is the following: process variables → sensorial perception → data processing and analysis → cognitive decision → action. Not covered is data transfer from sensor to the system processing the data and feature extraction. These data acquisition (DAQ) devices and data transfer protocols are fundamental to any sensor system, ranging from reading a simple voltage output signal to a more sophisticated (bidirectional) protocol, e.g., IO-Link.[2]

Figure 8.3 illustrates an approach that has been adopted at the University of Sheffield Advanced Manufacturing Research Centre (Dominguez-Caballero et al., 2019). Rather than storing all raw data in long-term storage, which incurs storage and networking costs, a short-term buffer is used for raw data, providing storage for a number of weeks, and then overwrites the earliest data. Edge-processed *summary* data is sent to a central database, either on-premise or cloud-based, for long-term

[2]https://www.io-link.com/en/Technology/what_is_IO-Link.php.

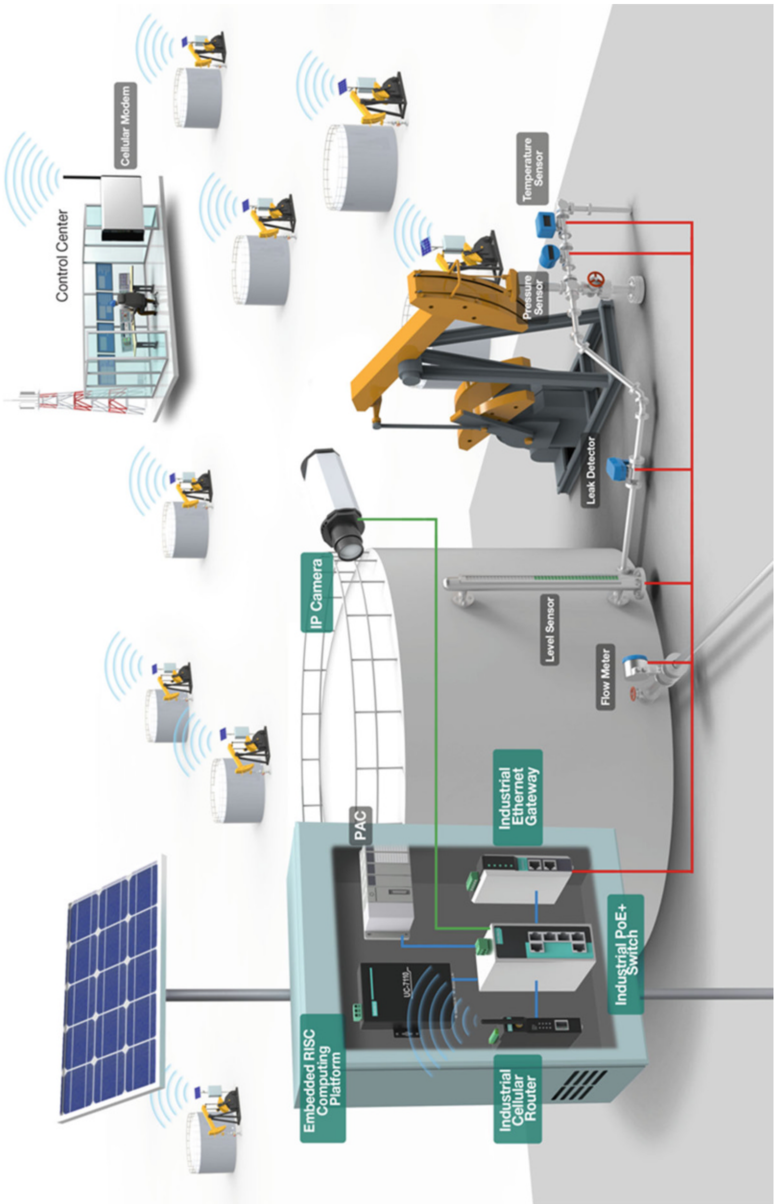

Fig. 8.2 An example of an IIoT system (Alcácer & Cruz-Machado, 2019)

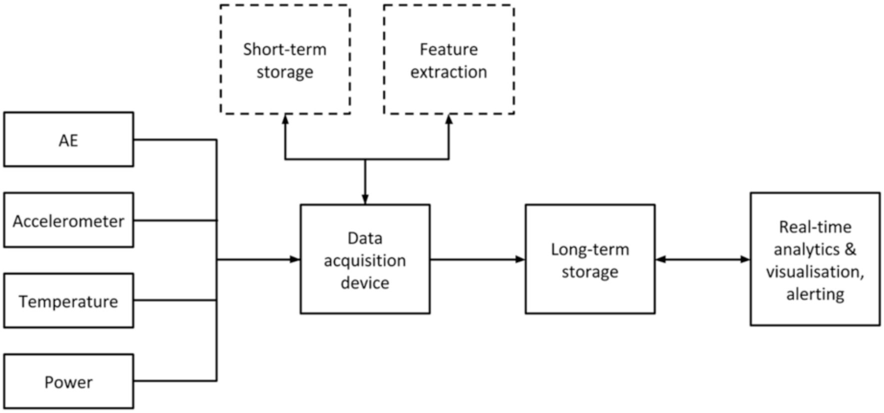

Fig. 8.3 Data flow from sensors to storage and beyond

storage and analytics. The edge processing of the raw data typically includes extraction of features in the time-, frequency-, and time-frequency domains.

Table 8.1 presents a summary of sensors or measurement types, their potential applications in manufacturing, and typical frequencies of data capture. The choice of which sensor to use is entirely dependent on the intended use case (e.g., predictive maintenance, environmental monitoring, process health, etc.), with some sensors being useful across multiple tasks. Fujishima et al. (2016), for example, use 24 sensing devices to monitor a machine tool and its processes for applications, including energy saving, predictive maintenance, and safety. Further example uses of sensing in smart manufacturing include the following.

8.2.1.1 Tool Condition Monitoring

Monitoring tool condition is an important, yet time-consuming, task in many machining scenarios. This is because the tool condition has a direct impact on the achieved surface quality and geometrical properties of a workpiece. Checking on tool condition usually involves a manual visual inspection by an operator or using a tool measurement system within the machine tool itself. Either way, the machining process must be stopped to perform these tasks. Therefore, there is a desire to automate the process, and the use of sensors provides a potential solution to this. Different sensing can be used to monitor tool condition. Prior literature has shown that cutting tool surface temperature is a key indicator of cutting process quality. Heeley et al. (2018) propose the use of temperature measurement to capture thermal data from as close to the cutting tool surface as possible. Another approach to measuring tool condition in situ is presented by Maier et al. (2018) who designed an Industry 4.0 tool holder, which incorporated strain gauges, to measure cutting forces during machining operations. An increase in the cutting force can be a

Table 8.1 Sensors and measurement types and their applications in manufacturing environments

Sensor/ measurement type	Applications in manufacturing	Frequency
Temperature	Factory environmental conditions, machine tool structure monitoring (potential deformation), cutting tool condition, motor and drive condition, component temperature (growth, shrinkage), additive process assessment	Typically, low (<1 Hz) High for cutting tool condition (>1 kHz)
Humidity	Factory environmental conditions	Low (<1 Hz)
Power	Machine tool motor and drive monitoring, building management systems	Low for general energy usage calculations (<1 Hz) Medium for asset health monitoring (<1 kHz)
Accelerometer	Machining vibration, spindles and bearings, floor vibration	High (1 kHz–20 kHz)
Force and torque	Machine tool structure and fixture monitoring, conveyor system monitoring, spindle and bearing monitoring	Low to medium (1 Hz–1 kHz)
Encoders, proximity	Position of guideways, rotary systems, robot arms, conveyor belt tension, etc.	Medium (<1 kHz)
Acoustic emission	Cutting tool condition	Very high (>50 kHz)
pH, composition, particulates	Fluids condition monitoring (e.g., metal working fluids for machining, fluid components in pharma and food)	Low (1 Hz or less)
Vision systems	Part identification, quality monitoring, asset identification and location, asset attendance	N/A

predictor of tool wear. Duro et al. (2016) propose a cost-saving approach to monitoring tool wear by using acoustic emissions (AE) data.

8.2.1.2 Machine Tool Health Monitoring

Machine tools are a core component of many manufacturing systems. If a machine tool fails, it can cause both irreparable damage to any component currently in process and significant delays. Therefore, monitoring the health of machine tools is a key activity of any smart manufacturing system, both for ongoing monitoring and proactive maintenance activities (Lee et al. 2018). There are many types of sensor that play an important role in machine tool health monitoring, and the choice of sensor depends on which element of the machine is to be monitored. For example, bearings can be monitored using vibration, force, and deformation sensing. Spindle health can likewise be monitored with vibration, as well as temperature and data from a machine tool controller. Determining which elements of a machine to monitor, and consequently choosing sensing devices, can be achieved using a Failure Modes and Effects Analysis (FMEA)—identifying where failures might occur and what these may be.

8.2.1.3 Additive Process Performance

Additive manufacturing (AM) is gaining popularity in all sectors as it has the potential to reduce material use, as only the required material is added to gain a near-net shape, as opposed to surplus material being subtracted. Furthermore, additive methods offer new ways for designing both the external and the internal structure of components, allowing increasingly complex designs to improve component quality, previously unattainable using traditional subtractive methods. Sensing plays a key role in ensuring that an additive process is performing as expected. Xia et al. (2020) provide a comprehensive overview of how sensing technologies can be used to monitor, and ultimately control, AM processes. They include details on how vision systems, spectroscopy, acoustic emission, and thermal data can assist in detecting various AM defects, such as cracks, porosity, voids, and surface defects.

8.2.1.4 Sub-surface Material Quality

In the high-value manufacturing sector, metallic components are typically machined from billets or forgings of raw materials. Understanding the material properties of the raw stock is paramount to ensuring the quality and longevity of the final product and often forms part of the final acceptance “sign off” for a component. The tests employed for capturing these material properties, either destructive on sample parts or nondestructive on almost all parts, are time-consuming and costly and in some cases rely heavily on chemicals with significant environmental footprints. One such test is chemical etching for grain size analysis, typically in titanium billets (a length of metal), which only captures a selection of billets due to the time and resources involved. Recent research has shown that force dynamometry data (measurement of force expended) contains enough information to accurately predict grain size during a machining process (Fernández et al., 2020), and embedding such techniques in machining processes would allow sub-surface quality to be captured in situ rather than as an additional manufacturing activity.

8.2.1.5 Legacy Devices and Low-Cost Sensing

Enabling Industry 4.0 and IoT technologies is expensive; therefore, these technologies are often not being adopted by small-to-medium enterprises (SMEs) because of

Fig. 8.4 Colchester Bantam lathe with a low-cost Industry 4.0 solution (Lockwood et al., 2018)

cost and a lack of expertise within those companies.[3] Many of these SMEs can see the value in digital technology in their business, in particular when many of the assets being used in daily production are considered *legacy* devices—usually translated to “old,” but can actually refer to devices that are 10 years old or less. What is common across legacy devices is a lack of connectivity and data capture capability. This makes Industry 4.0 adoption challenging for those SMEs that predominantly use legacy devices.

In 2018, a project was undertaken at the University of Sheffield Advanced Manufacturing Research Centre (AMRC) to digitize legacy devices, thus demonstrating that it was possible and did not need to be prohibitively expensive (Lockwood et al., 2018). The project took two legacy machine tools, a Colchester Bantam lathe (c. 1956) and a Bridgeport Turret Mill (c. 1980), and installed both low-cost (<£500) and high-cost (<£5000) sensing systems. The data captured was used to populate a web-based dashboard that informed on overall equipment effectiveness (OEE), operating cost, machine condition, and process condition. The lathe with the dashboard is shown in Fig. 8.4, along with an operator viewing critical data on a mobile device.

[3] https://www.gov.uk/government/publications/made-smarter-review.

8.2.2 Smart Hand Tools

Modern manufacturing environments are implementing more automation and making use of robotics to assist and speed up processes; however, manually operated hand tools are still commonplace. Use of hand tools can range from setting parts in a machine tool fixture to assembly of components, or for maintenance operations. It is unlikely that robots will completely replace the use of hand tools, and therefore manual operations using them can be part of the smart manufacturing paradigm. Indeed, these operations offer perhaps the greatest opportunity to move from processes in which no data is captured, or is simply verified, to processes where accurate measurements and records are made and stored. "Smart" hand tools are tools that have some element of sensing and connectivity built-in, allowing necessary parameters to be captured. For example, a smart torque wrench when combined with digital work instructions are "aware" of current operations, allowing appropriate torque limits to be set remotely.[4] Sequences of operations can also be programmed to allow a series of torque values to be worked with. Communication is two-way: not only can torque values be set, but the torque values actually achieved can be stored, thus avoiding manual recording of results where errors can creep in.

There are immediate benefits in using smart hand tools in manufacturing. The reduction in recording data manually, either check boxes for correctly set torques or measurement results, leads to more reliable data capture. Furthermore, the event data is digitized immediately, allowing it to be combined with other process data, providing a digital paper trail. For workers, reducing administrative tasks in measurement data capture means that skilled operators can get on with the tasks that actually require their skills.

8.2.3 Location Tracking Technologies

Knowing the location of an object in a manufacturing environment can save significant time and cost. This applies to both knowing the location of a component or part and other assets that are essential to the manufacturing process. There are a number of technologies that can assist with locating objects, allowing tracking to take place at the local through to the global level. For example, printed codes that are read by a scanner, such as QR codes and barcodes, are common in many manufacturing facilities.

The ability to quickly scan a code to log the location of an object allows production to be tracked with high fidelity. Printed codes also allow users to quickly retrieve electronic information about an asset, or to input data to an object's data store. A challenge with scanning printed codes for location tracking is the reliance on busy operators to perform the manual scanning process, often in the midst of busy

[4] https://www.facom.com/uk/products/Smart-Torque-Description.html.

production environments. Better is the use of automated location tracking technologies. Radio-based technologies, including RFID, WiFi, and Bluetooth, can be used for passively tracking the location of almost any manufacturing asset. Not only is this useful for updating a manufacturing execution system (MES) on the progress of a part in real time (Yang et al., 2016), but such technology can also be used to find the approximate location of tools, fixtures, lifting equipment, etc. This would mean that engineers are not spending their time looking for missing objects in busy workshops.

As well as tracking items at the local level, location technologies can be used for tracking across multiple buildings at a site (e.g., using LoRaWAN), or for tracking on a much wider scale using GPS. The latter, combined with 2G and 3G wireless networks, could be particularly useful for providing near-real-time updates on the location of parts from suppliers headed toward a manufacturing facility. The same applies for keeping customers updated on the location of shipped finished products. Location technologies can also play a significant role in the health and safety of the workers, e.g., stopping a robot in a cell if a person enters that cell.

8.2.4 Industrial Machinery Connectivity

All smart manufacturing scenarios include machinery that is connected to the overall architecture and has data captured from it. Such machinery is typically controlled by a PLC (Programmable Logic Controller), and may be connected to other systems and machines using, for example, SCADA (Supervisory Control And Data Acquisition) technology. Where a manufacturing plant contains machinery from many different equipment manufacturers who may all have their own proprietary protocol for capturing data, there will be challenges in retrieving data from machine controllers.

There have been efforts to overcome the incompatibility challenge by developing standards and protocols that can be applied across any control system. For example, the MTConnect standard[5] proposes a method of communicating data from controllers and sensors that is based on eXtensible Markup Language (XML), a data format that is easily interpretable and follows a clearly defined structure. Another standard that is widely used to facilitate equipment connectivity is OPC-UA.[6] Described as a "platform independent service-oriented architecture," OPC-UA is natively available on equipment from many industries including oil and gas, pharmaceutical, and building systems, as well as manufacturing. The openness of OPC-UA makes it a very flexible standard that allows it to handle most equipment data transfer needs.

Lu et al. (2020) provide an excellent overview of the many connection standards that currently exist in manufacturing, ranging from what the authors refer to as the

[5]https://www.mtconnect.org.

[6]https://opcfoundation.org/about/opc-technologies/opc-ua/.

field (i.e., shop floor connectivity) through to enterprise resource planning (ERP) systems. With regard to IIoT, Lu et al. provide the landscape as illustrated in Fig. 8.5. The authors highlight that the "…wide variety of connection options can be applied to meet various requirements of smart manufacturing applications…" but also point out that carefully structuring the data and information being shared is critical to the success of Industry 4.0. Additional shop floor connectivity is now offered by a new breed of industrial PCs coming into the realm of asset data capture. These PCs have capability for both acquisition, processing, forwarding to persistent storage, and even triggering an action on the asset. Such PCs are referred to as edge devices or gateways and vary in capability, size, operating system, connectivity options, and so on. However, one thing that all edge devices have in common is the desire to bring actionable insight to the shop floor as quickly as possible. Such edge devices are aligned with the desire to move to cloud-based services (see Sect. 8.3).

8.2.5 Moving to Wireless Connectivity

Connectivity in many manufacturing environments still relies heavily on a physical connection between devices. Therefore, infrastructure must be in place to provide cabling, connectivity management, and security. Wireless technologies can ease this challenge by removing the need for physical connection. However, simply moving to a wireless network using WiFi will still require considerable management and could introduce conflicts between Information Technology (IT) and Operational Technology (OT) system bandwidth. Furthermore, a standard WiFi network is range-limited and only able to function where devices are in reach of a router and so cannot be used for communication beyond the factory. As such, technologies such as Low-Power Wide Area (LPWA) networks, LTE-A, and 5th Generation mobile networks (5G) offer a number of advantages over standard wireless networking solutions. Of these, 5G is most commonly associated with being the solution of choice as it is a modern, future-looking option.

The benefits of 5G for manufacturing are emphasized on Ericsson's Insights pages.[7] 5G communication also features heavily in many scholarly articles discussing Industry 4.0, the Fourth Industrial Revolution, and IIoT. Its uses range from time-critical process control and health monitoring across many assets and sites, combining with AI to enable a "learning factory" (Zhang et al., 2020). As such, it is inevitable that any smart factory of the future will rely on 5G communication. This is further illustrated by the "5G Factory of the Future" research project[8] funded by the UK5G Innovation Network, launched in August 2020. With a value of £9.5 million (sterling), the project aims to address some of the key challenges in

[7]https://www.ericsson.com/en/networks/trending/insights-and-reports/5g-for-manufacturing.

[8]https://uk5g.org/discover/testbeds-and-trials/5g-factory-future/.

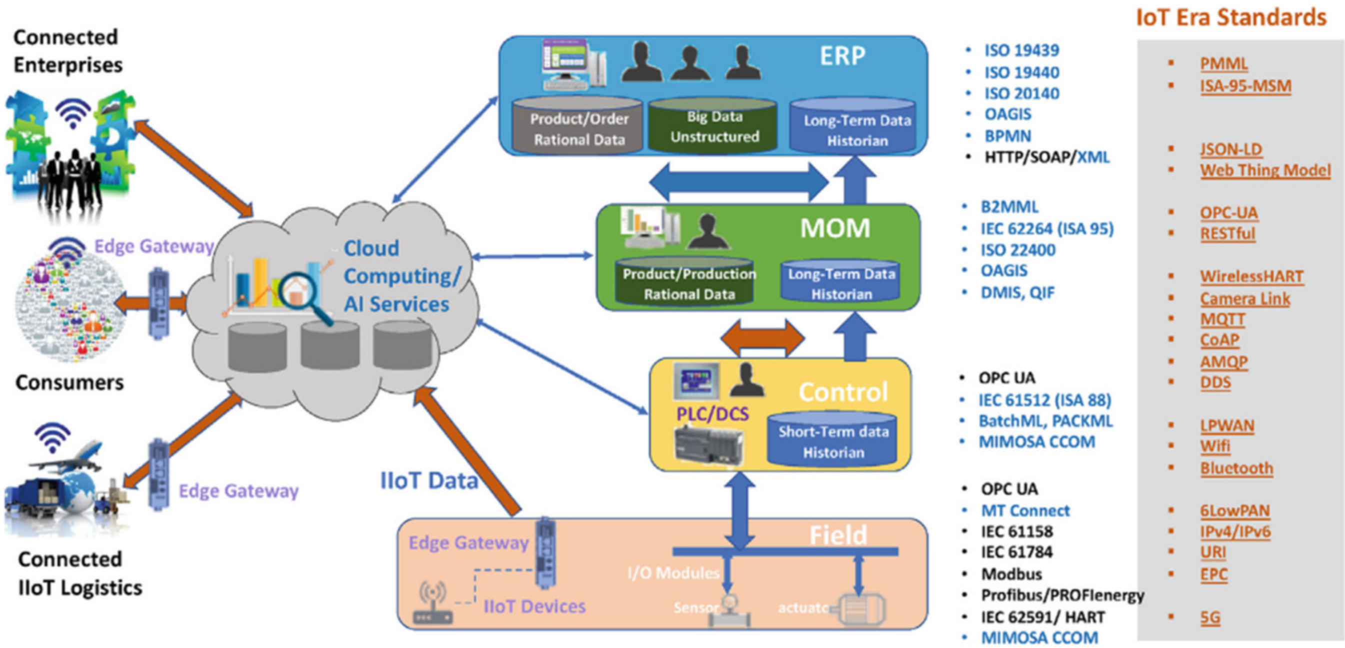

Fig. 8.5 The IIoT era integration standards landscape (Lu et al., 2020)

deploying 5G in manufacturing, testing use cases such as robotic assembly, reconfigurable assembly lines, and distributed augmented and virtual reality.

8.3 From Sensors to Business Value

An important attribute of manufacturing is captured by the notion of *value chain*—the interlinked resources and processes that go from raw materials to value-added products. In smart manufacturing, data is key to transformation and, therefore, must be managed as an asset. The generation of data, its storage and governance, and subsequent analysis and use are captured by the *data value chain*. In this section, we discuss core technologies that support data management, data analysis, insight, and automation in smart manufacturing.

8.3.1 Cloud Computing

Increasingly in business, cloud-based technologies are being adopted to provide scalable and flexible solutions. The infrastructure must also provide appropriate networking, connectivity, gateways, and standardized interfaces along which the data can flow. In manufacturing, the use of cloud-based solutions (provision of computing resources over the Internet) enables businesses to outsource their IT resources and offers a scalable, integrated, and centralized store for manufacturing data, such as multiple IIoT devices, where data can be ingested, transformed, and analyzed in real time and at Big Data scale. Cloud manufacturing (CMfg) has been proposed as a concept that uses cloud computing technology (computing and service-oriented technology) to improve current manufacturing systems (Alcácer & Cruz-Machado, 2019). There are many benefits of utilizing cloud-based solutions and for smart manufacturing, including (1) cost-effective and dynamic access to large amounts of computing power, (2) almost immediate access to hardware resources without upfront capital investments, (3) lower barriers to innovation, (4) easy dynamic scaling of enterprise services, and (5) enabling of new classes of applications and services (Schmitt et al., 2020).

However, despite the benefits, cloud computing also offers several disadvantages, such as network latency and bandwidth issues, performance issues with multiple customers and applications running on the same infrastructure, and issues around security, such as regulatory compliance and governance through the use of external third-party providers. The use of edge computing is often used to reduce the potential bottleneck arising from large volumes of data and use of cloud computing by performing computations at the data source. These devices can consume and produce data; handle computing tasks, such as processing, storage, caching, and load balancing and exchange data with the cloud; as well as incorporate AI capabilities to perform predictions locally (rather than having to interact with the cloud).

8.3.2 Big Data Analytics

To support smart manufacturing requires substantial compute power and networking infrastructure to handle data being generated in real time by sensors and actuators. However, data have not just grown in terms of *volume* and rate of production (*velocity*); data have also changed in terms of *variety* (range and types of data sources) and reliability (*veracity*). Being able to process multiple forms of data in real time and offer real-time decision support requires (Big Data) computational systems to gather, store, manipulate, and analyze data, for example, distributed data storage and advanced analytical methods (Oussous et al. 2018; Gao et al., 2020). Other attributes of Big Data that have emerged within Industry 4.0 include *validity* (correctness of data), *volatility* (tendency to change in time), and *vulnerability* (to breach or attacks).

The use of techniques from across disciplines is common (e.g., Computer Science), including methods for various types of data analysis, e.g., descriptive, diagnostic, predictive, and prescriptive. Although existing statistical methods can often be used, the characteristics of Big Data also call for alternative methods. For example, dealing with *uncertainty* is a situation which involves unknown or imperfect information (e.g., noise in sensors), and methods, such as Bayesian theory or probability or belief function theory, are often used (Hariri et al., 2019). The process of extracting insights from Big Data can be broken down into stages for data management and analytics (Gandomi & Haider, 2015).

Being able to process large volumes of data in real time has led to advances in data management and processing, e.g., the use of distributed files systems, parallel processing technologies, and ingestion of streaming data (Oussous et al. 2018). In many scenarios, Apache Hadoop has become the de facto open-source standard for sharing and accessing data. Figure 8.6 summarizes a generic Big Data architecture, whereby data sources (batch and real time) are ingested into centralized storage (e.g., a data lake). Real-time data is handled separately from data loaded in batch and using stream processing. Machine learning is often used for tasks, such as predictive analytics, and results stored in an analytical data store (e.g., data warehouse or SQL database), which can be used for analytics and reporting.

The architecture in Fig. 8.6 can often be seen in manufacturing examples. For example, Fig. 8.7 shows the use of Microsoft Azure for IoT and Big Data analytics[9] with a number of core Azure components. Data is ingested in batch (e.g., maintenance logs) using *Azure Data Factory*, an Azure component for orchestrating data ingest and transfer, or as streaming data (e.g., IoT or sensor data) using *Azure IoT* or *Event Hubs*—these enable a security-enhanced bidirectional communication between IoT applications and devices. Real-time streaming data will typically be stored in the *Azure Data Lake,* a massively scalable data store that includes security and auditing functionality. As the data is pre-processed and transformed (in this case using *Azure Databricks*), refinements of data will be stored back in the data lake in

[9]Example of Azure architectures: https://docs.microsoft.com/en-us/azure/architecture/browse/.

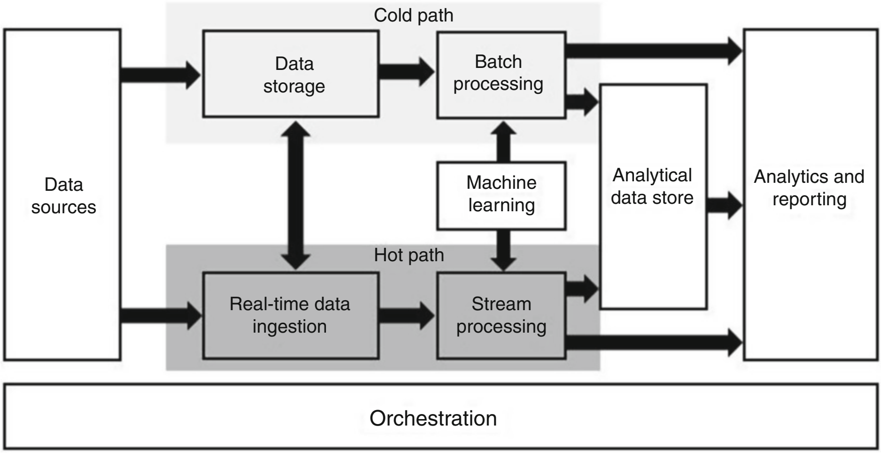

Fig. 8.6 Generic Big Data analytics infrastructure (Based on: https://docs.microsoft.com/en-us/azure/architecture/data-guide/big-data/)

separate zones (raw, enriched, and aggregated). Non-streaming data can be ingested in batch using *Azure Data Factory* and also stored in the data lake. *Azure Databricks* and *Azure Machine Learning* can be used for tasks, such as predictive analytics. In Fig. 8.8, *Azure Synapse* provides a data warehouse and analytical functionalities. Real-time analytics is provided using *Azure Data Explorer*. Finally, reporting and dashboards are provided with *Power BI*.

8.3.3 Artificial Intelligence

Perhaps one of the biggest drivers of disruptive innovation has been the rise in artificial intelligence (AI) technologies, especially machine learning (ML). In manufacturing, coupling AI with data generated more widely across the manufacturing process and the evolution of robotics and autonomous systems and agents is enabling the *automation* of data-driven decision-making in production and service delivery. AI uses computational methods to encapsulate and mirror human intelligence, allowing a nonhuman system to learn from experience and imitate human intelligent behavior, typically using machine learning. The combination of AI techniques, especially *deep learning*, with developments in other areas, such as semantic computing, robotics, and computer vision, is enabling Industry 4.0. For example, AI and the Internet of Things, Web of Things, and Semantic Web are enabling the vision of Industry 4.0, e.g., the Semantic Web of Things for Industry 4.0 (SWeTI) platform proposed by Patel et al. (2018).

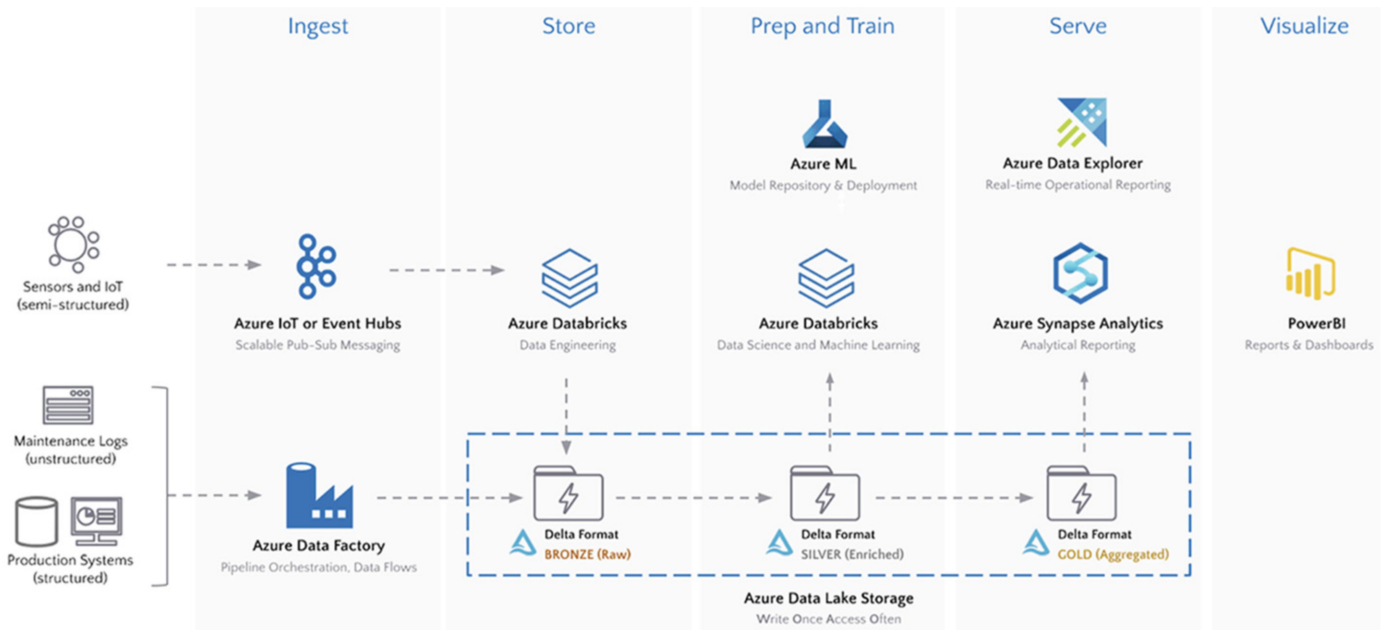

Fig. 8.7 An example of a Microsoft Azure architecture for IoT and Big Data analytics (source: Databricks, https://databricks.com/blog/2020/08/03/modern-industrial-iot-analytics-on-azure-part-1.html)

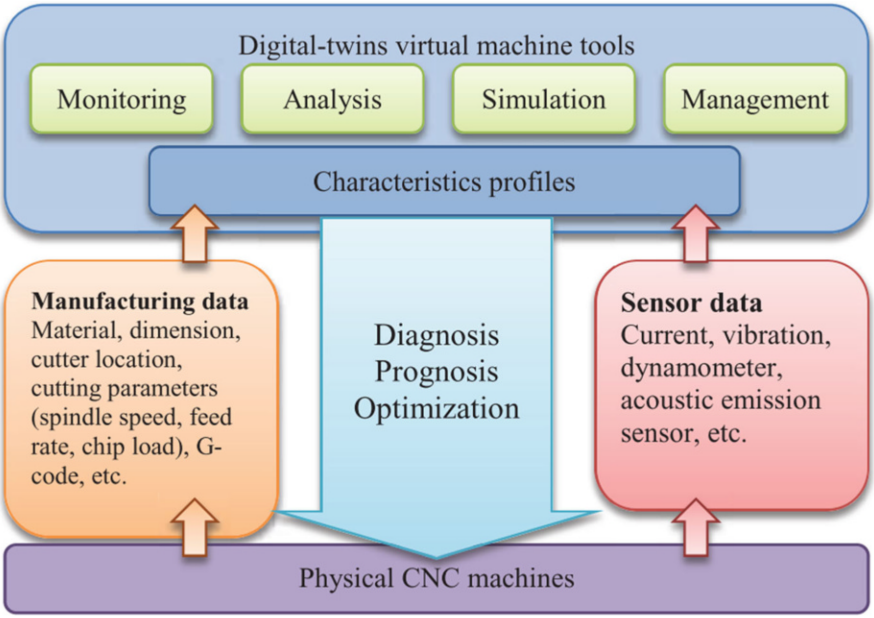

Fig. 8.8 Digital twin sensor and data fusion concept (Cai et al., 2017)

In manufacturing, the use of AI is considered critical to future success. For example, in a 2018 survey on AI by Forbes Insights,[10] 44% of respondents (from the manufacturing and automotive sectors) considered AI as "highly important" to the manufacturing function in the upcoming 5 years. A further 49% deemed it as "absolutely critical to success." Common uses include (a) predictive maintenance, (b) collaborative and context-aware robots, (c) yield enhancement in manufacturing, and (d) automated quality testing. The 2020 Capgemini report "Scaling AI in manufacturing operations: a practitioners' perspective"[11] goes further and identifies even more use cases (Table 8.2). The Capgemini report states that machine maintenance and quality control are the leading transformative AI projects in manufacturing operations, along with increasing use of robotics.

8.3.3.1 Predictive Maintenance

Predictive maintenance (PdM) is seen as one of the top manufacturing use cases for AI as "the impact of maintenance represents a total of 15 to 60% of the total costs of operating all manufacturing" (Zonta et al., 2020:2). PdM is the application of

[10] http://forbes.com/sites/insights-intelai/2018/07/17/how-ai-builds-a-better-manufacturing-process/#7aa455621e84.

[11] https://www.capgemini.com/research/scaling-ai-in-manufacturing-operations/.

Table 8.2 Example of AI use cases in manufacturing operations (Capgemini[11])

Function	Use cases
Product development/ R&D	• New product development • Product validation in R&D • Product enhancement
Demand planning	• Demand planning/forecasting
Inventory management	• Order optimization • Standardized communications with suppliers using Natural Language Processing (NLP) Inventory planning
Process control	• Real-time optimization of process parameters • Optimize equipment changeover
Production	• Optimizing overall productivity in production line • Reduction in Takt time • Computer vision for product identification • Layout planning • Collaborative robots (cobots)
Quality control	• Product quality inspection • Predicting final product quality
Maintenance	• Intelligent maintenance • Energy management • Spotting anomalies in communication network • Worker safety • Scrap/wastage reduction • Increasing equipment efficiency

predictive analytics that can assist many industries, not just manufacturing, to utilize assets (e.g., manufacturing and computing equipment, aircraft engines, turbines, etc.) in the most efficient way and thereby reduce costs associated with downtime and defective products. AI, in particular machine learning, can be used for common maintenance tasks, such as fault diagnosis, predicting mechanical failures and Remaining Useful Life (RUL), and maintenance scheduling to support planned equipment downtime. Using predictive analytics offers a more *proactive* rather than *reactive* approach to maintenance: *corrective maintenance* replaces parts when they fail, *preventative maintenance* determines useful lifespan for a part and replaces it before a failure, and *predictive maintenance* enables just-in-time replacement of components.

Machine learning methods, especially neural networks and deep learning approaches, are commonly used in predictive maintenance applications to examine relationships between data points and the labelled output (e.g., failures) and build models to predict such outcomes (Zonta et al., 2020). Historic data can therefore be used to recognize patterns from past events and enable manufacturers to predict future failures or prevent them based on learning from the root causes of the breakdown events. Predictive models can be used to predict machine breakdowns, and historic training data could include sound to detect anomalies in device operations, sensors to detect changes in operational conditions (e.g., temperature, vibrations, etc.), or IoT divided integrated into manufacturing equipment or processes.

Additional data sources may also be used and input to machine learning, such as maintenance logs, quality measurement of machine outputs, and external data sources (e.g., weather).

8.3.3.2 Identifying Defects and Quality Control

The demand for consistently high quality within manufacturing processes and products has driven the use of innovative methods, including AI, to enable reliable quality inspection. Common approaches to quality improvement include *visual inspection methods*, e.g., monitoring parts or mechanical processes, such as welding or soldering, on a production line. Traditionally, quality control is time-consuming if performed manually where specialists must test products for defects. The introduction of image recognition technologies enabled manufacturers to identify potential flaws based on sets of predefined conditions or rules.

Automated visual inspection approaches typically compare (pixel by pixel) a reference image of a product with a selected image for inspection. However, such methods can suffer from issues with imperfect lighting conditions or variations in product mounting during inspection that cause differences between the selected image and reference version. The use of computer vision and AI can overcome these issues as models become invariant to differences in testing conditions and can focus on the patterns within the image which represent quality issues, such as defects. This has enabled algorithms to learn the features of a "good" product and, after training, to recognize different types of defects automatically, e.g., identifying defects in surfaces, typically in combination with existing quality checking processes (human and automated). For example, Schmitt et al. (2020) describe a quality assurance approach for a printed circuit board (PCB) whereby a predictive model is used to determine which PCBs to test with an existing automatic optical inspection (AOI) system (i.e., an X-ray inspection system). The rationale is that due to the high volumes of production, it has become a bottleneck in the process. The predictive model, trained on data gathered from PCB examples and an outcome of OK or Not OK (NOK), classifies the PCBs, and any that are categorized as NOK are then sent to the X-ray inspection unit. This reduces the bottleneck and improves product quality as only suspected faulty boards require further verification.

8.3.3.3 Robots and Automation

Advances in mechatronics, computing, and communication technologies are driving the field of modern robotics and autonomous systems. Stand-alone industrial robots have been central to automation in industries, such as aerospace and automotive, in transforming production by replacing or assisting humans in performing various manufacturing tasks, since first appearing in the 1960s. Recent advances have seen the development of collaborative robots (or "cobots")—robots designed and built to collaborate with humans and work alongside them (Hentout et al., 2019). Another class is mobile robots or automated guided vehicles (AGVs), commonly seen in warehouses and distribution centers and used to move objects between machinery or machinery. The use of advanced sensor, location, and camera technologies is being coupled with AI to provide robots with the intelligence to be able to navigate and work unaided by humans.

8.4 Beyond the Physical World

In Sect. 8.2, the discussion focused on connectivity and monitoring of physical assets and processes within manufacturing systems. It was highlighted that the data from such activities can yield new actionable insights that were previously unknown, and this is especially true when the data is fed into AI systems (Sect. 8.3). An additional use for such data is to feed into systems that take the user beyond the physical world and into the realm of digital twins, extended reality, and manufacturing process simulation.

8.4.1 Digital Twin

A recent report published by the University of Sheffield Advanced Manufacturing Research Centre (Eyre et al., 2020) defines a digital twin as: “A live digital coupling of the state of a physical asset or process to a virtual representation with a functional output.” The report breaks down the key elements of this statement, namely, that:

- The data is *live*, or as close as is acceptable to live
- There is a *digital coupling* to transmit data over a digital carrier medium
- The *state* of the system is the condition of the system or process at a given time
- There is a *physical asset or process* that the digital representation is linked to, as opposed to a simulation or a reply of an event
- The *virtual representation* is analogous to the physical thing
- There is a *functional output* from the digital twin, such as information transmitted to a system or human that can take action on the output, to deliver some value

The above definition implies that the digital twin has a purpose and will deliver value to a manufacturing asset or process, rather than simply acting as marketing material or a dumb simulation. This definition is in contrast to the idea of a digital twin as proposed by Cai et al. (2017) and illustrated in Fig. 8.8. The authors discuss how sensors and other data streams can be used to feed a “digital twin” as a model of a virtual machine tool. There is no proposal that the data is live, but rather the data can be used for prognosis and diagnosis of machine or process faults. Gao et al. (2020) also define the digital twin as “. . .an emerging concept that leverages data and information collected from a physical system to create a digital representation of that system that may be used to generate some desired control action.” The authors discuss how data can be fed into a digital twin to optimize performance, predict maintenance-related faults, and virtually verify or validate equipment.

There is no mention of the digital twin being a live representation; when a digital representation is fed data in a unidirectional way, this is sometimes referred to as a *digital shadow* (Kritzinger et al., 2018). Maier et al. (2018) provide an example of a digital twin that provides real-time feedback based on sensor data. The authors developed a system for monitoring the wear of a cutting tool to be used in a machining process. Importantly, for our initial definition of a digital twin, the data is presented live to the machine tool operator with some indication of what the data means. As such, the operator can take action as needed. This example highlights that a digital twin can be of almost anything, such as a tool, single process, a complex machine tool, a production line, or even numerous global facilities.

8.4.2 Extended Reality

Technologies that extend reality, either fully through virtual reality (VR) or partially through augmented reality (AR), are commonplace in the consumer market and are starting to gain traction for what they can offer in industrial settings. In a 2018 report, Gartner predicts that 70% of businesses will be experimenting with immersive technologies, but it is likely that only 15% will have deployed them into production.[12] Virtual reality provides a fully immersive digital environment; augmented reality is the use of digital overlays of information on the physical world, but with very little interaction with the virtual objects. Mixed reality is a true blend of the virtual and physical worlds, allowing users to interact with both real and virtual objects. Such technologies are not new. For example, Caudell and Mizell (1992) proposed an augmented reality heads-up display (HUD) to assist manual manufacturing processes (e.g., guide operators to correct drilling locations). Modern AR use cases in manufacturing still include guiding shop floor operators in assembly, maintenance, or quality control tasks, as well as enhancing training experiences (Syberfeldt et al., 2017). The key difference now is that AR is available on many more devices, such as smartphones or tablets, as well as more advanced and lightweight AR glasses.

Another key reason for increasing interest in the use of AR is the amount of data being captured in manufacturing environments and how this data can be presented through AR technology. For example, a modern maintenance engineer can use AR technology to guide them to the source of an issue, as a result of sensor readings within a machine tool. The AR technology can also guide the maintenance engineer to complete the task more quickly. Another use case based on volume of data could be providing shop floor supervisors an overview of current production activity and

[12] https://www.gartner.com/en/documents/3881066/virtual-reality-and-augmented-reality-using-immersive-te.

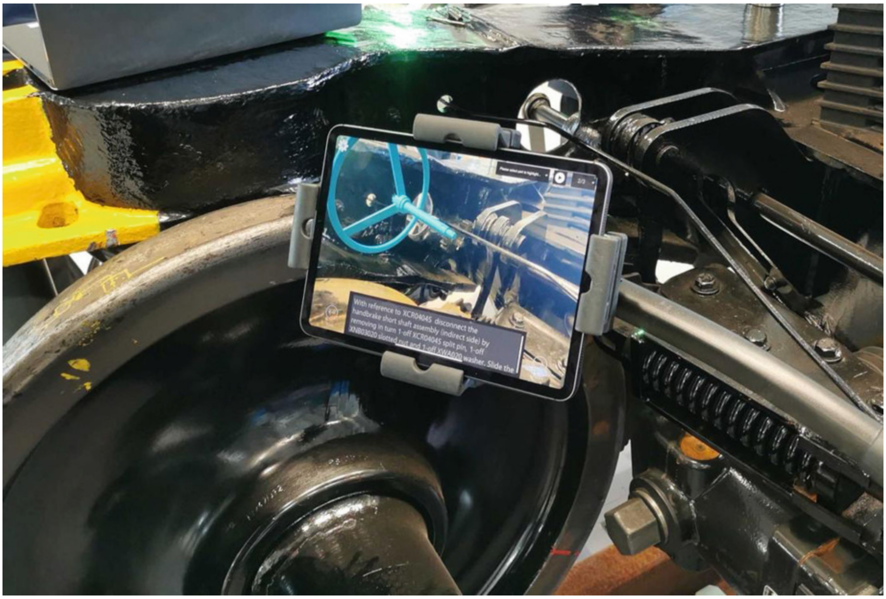

Fig. 8.9 Example of an AR overlay for identifying service and maintenance items on a train chassis

capacity by donning a pair of AR glasses and looking around their shop floor to identify any challenges. Through a connection to a central data store, the glasses could present the supervisor with real-time information on equipment status and product locations. Virtual reality completely immerses uses in a virtual world, with no visibility of the real world around them. Instead, the user is presented with a 3D virtual world in which they can explore and interact with objects, usually through handheld controllers.

The example shown in Fig. 8.9 demonstrates how AR has been applied at the AMRC for identifying and instructing maintenance tasks on a train chassis. This same technology can be applied in a manufacturing setting for both maintenance and assembly. There are a number of uses for VR in manufacturing, including training and practicing procedures which can be costly in the real world, or visualizing component or even factory designs before they are first created in the real world and more clearly than using 2D drawings.

8.4.3 Simulating Manufacturing

Simulation in manufacturing can mean many different things—simulating stresses on a part design, simulating a machining process, simulating an assembly, simulating how the tooth of a tool interacts with a material it is cutting, simulating complete production flow in a factory, or all the way through to simulating supply chain and logistics (Mourtzis, 2020). Simulation that relies on a model of a system (where the model is based on analytical, numerical, or mechanistic methods) can be improved through observation of experimental results, with the model updated based on findings. However, with the increase in data capture through IIoT technologies, simulations can now more easily be compared and contrasted against real-world results, and ultimately simulations can be improved by incorporating actual process data into the simulation design. This data-driven manufacturing paradigm can update manufacturing simulations using the data sources and capture methods discussed in Sect. 8.2, and either update a model automatically or omit the modelling altogether, using the result of AI algorithms to influence the manufacturing system.

Simulation can be coupled with many other technologies discussed in this chapter. An example of combining simulation with real-time data can be seen at the Boeing factory in Sheffield, UK (Hughes, 2018). Before the layout of this facility was finalized, a complete model of the factory was developed as a simulation (specifically discrete-event simulation—DES) to model a number of production scenarios and "what-if" situations. The model was also viewable as a 3D representation through a virtual reality system, so Boeing manufacturing engineers could test the layout of the production environment.

8.5 Summary

Manufacturing is an important and well-established industry and for decades has been implementing the latest methods and technologies. Recent developments in connected devices, the generation of vast quantities of data, and advanced manufacturing techniques are accelerating progress in manufacturing (Tao et al., 2018; Kusiak, 2018; Zheng et al., 2018), providing new opportunities for transforming manufacturing processes and improving products and services. However, despite the many benefits, there are also significant challenges to tackle (Al-Abassi et al. 2020). For example, in manufacturing in general, the adoption and implementation of new technologies and methods, developing sustainable processes, and adapting to new innovations are challenging. Besides these, smart manufacturing may also present the following challenges:

- *Acceptance and change*—data-driven transformation may require significant changes to existing manufacturing processes, job roles, technologies, and ways of working that have to be managed appropriately.
- *Integration*—implementing new technologies, such as cloud computing and AI, and integrating them into existing legacy business infrastructure and processes is challenging and costly, maybe requiring new skills and staff.
- *Security*—the importance placed on data means that security is a key concern in manufacturing where espionage, unwanted data access, or cyberattacks are potential issues with using the Industrial Internet and cloud-based digital systems.

- *Big Data*—the volume of real-time data produced by IIoT typically surpasses the capabilities of existing infrastructure, and therefore, new data processing and management systems are required. This can mean in practice significant financial investment.
- *Re-skilling*—existing job roles may be changed with the introduction of smart manufacturing, and there may be overall a lack of skills within manufacturing organizations to manage and take advantage of smart technologies. There is a shortage of qualified people to recruit with the right digital skills that can support data-driven projects.

Review Questions

- How would you define smart manufacturing (or Industry 4.0)?
- How can technologies, such as AI and augmented/virtual reality, be used to make manufacturing smarter?
- Within a factory, what kinds of data might be generated and collected for smart manufacturing?
- How can data collected within manufacturing be used to generate business insights?

Discussion Questions

- Manufacturing is a long-established practice and has often used new technologies and methods in innovative and smart ways. What then is different, or unique, about the new Industry 4.0 era?
- How can smart technologies be integrated into a factory? What are some of the challenges of doing this?
- What skills and knowledge might the engineers and technicians working in manufacturing in the future require?

Problem Statements for Young Researchers

- What are the benefits that smart manufacturing could bring to a company, to workers involved in the manufacturing process, to consumers of the products created, and more widely to society? What are the potential barriers faced in implementing Industry 4.0 and making manufacturing smart? Are there any short-term and long-term negative consequences or disadvantages of smart manufacturing on businesses, workers, national economies, or the environment?
- In what ways can you effectively and efficiently model real-time factory environments, and what are the opportunities afforded?
- Smart manufacturing allows organizations to gather and utilize data from the entire lifecycle of the product (the so-called digital passport). How can this be achieved in practice, and what are the likely challenges in doing this?

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