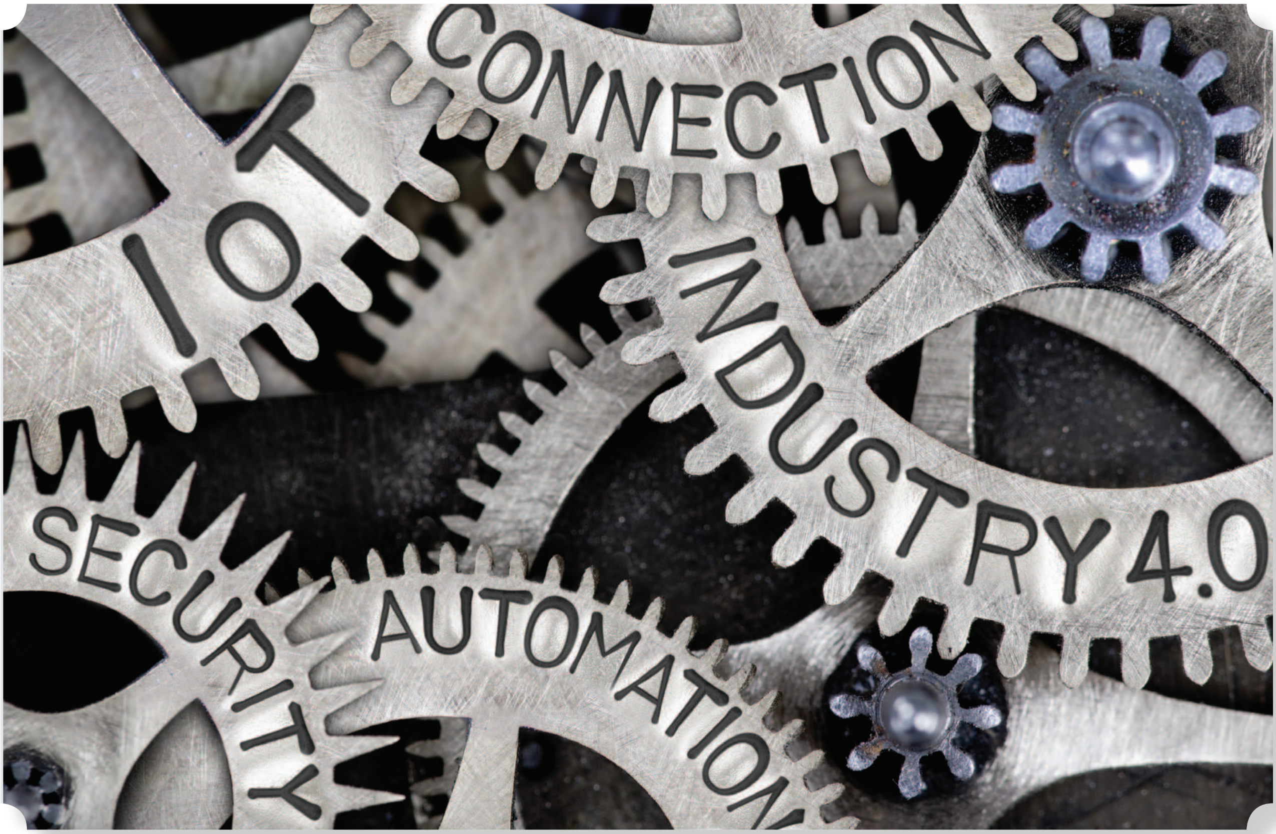
# The Internet of Things in Manufacturing

## Key Issues and Potential Applications

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With the globalization of the world's economy, manufacturing enterprises are facing severe competition from their worldwide counterparts in terms of product price, function, quality, cost, and lead time. They are also experiencing growing pressure to meet higher environmental standards due to enhanced producer responsibility [1]. Meanwhile, consumers have more diversified and demanding needs, e.g., customized products. These challenges have pushed the

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manufacturing industry to embrace new technologies to remain competitive and meet user demands. The Internet of Things (IoT), which has great potential in transforming the manufacturing sector [2], has attracted tremendous attention from both academia and industry.

The IoT envisions the seamless interconnection of the physical world and cyberspace and their pervasive presence around us [3]. It extends the Internet into the physical realm through the widespread deployment of spatially distributed devices with embedded identification (ID), sensing, and actuation capabilities [4], [5]. The embedding of tiny electronics into physical objects and networking them make them intelligent and seamlessly integrated within the resulting cyberphysical infrastructure. Thus, the IoT can enable a greatly enhanced horizontal integration of the various manufacturing resources/capabilities used in different stages of manufacturing and business-planning processes. Additionally, it can allow a vertical integration at different hierarchical system levels [6]. This provides unprecedented opportunities for existing or whole new manufacturing services and applications to leverage such advanced interconnections. For example, the connectivity between smart machines, warehousing systems, and production facilities will enable them to autonomously exchange information, trigger actions, and control each other independently [6].

The IoT envisions the seamless interconnection of the physical world and the cyberspace and their pervasive presence around us.

Furthermore, the pervasive sensing ability of IoT systems gives rise to a generation of huge and diverse volumes of data, which can be utilized to assist optimal decision making on various aspects of manufacturing activities. The manufacturing data sets are still growing rapidly because the density of sensing and actuation coverage is still in the early stages of development, and many more IoT devices will be deployed [7]. Cloud computing and big data technology are essential and play fundamental roles in managing huge amounts of manufacturing resources, and they provide highly elastic and scalable services to users, such as the powerful capabilities for storing, processing, and visualizing manufacturing big data [8]. The results from big data analytics allow manufacturers to better capture business opportunities, readily adapt to changes, and deal with uncertainty promptly.

This article provides an overview of key issues in IoT-enabled manufacturing and discusses some potential applications. Here, we do not distinguish the IoT from cyberphysical systems and adopt the IoT as a general concept, even though they do have some differences. Also, it should be noted that the research issues discussed are representative rather than complete. Some survey papers on the IoT's core technologies can be referenced, such as [9] on wireless sensor networks, [10] on cloud computing, and [11] on big data. These papers have provided good technical reviews; however, while economic aspects play a vital role in technical advancements and transformation, discussions on them are largely missing. Moreover, the manufacturing sector has its own domain-specific problems to be addressed when leveraging the power of the IoT.

## Background and Enabling Technologies

The wide adoption of the IoT in manufacturing has a close relationship with the development of IoT technologies. There are some core technologies that play vital roles in the IoT and can benefit the manufacturing industry tremendously.

### Radio-Frequency Identification

Radio-frequency ID (RFID) uses electromagnetic fields to transfer data for the automated identification and tracking of tags attached to objects [12]. RFID systems consist of RFID tags and readers. The tags attached to the objects hold information about the objects, while readers can decipher such information (including the unique IDs) without requiring a line of sight and report it to the enterprise information system. Therefore, the readers can indirectly track the physical movement of the tags in real time and thereby that of the objects to which the tags are attached. In manufacturing, RFID can be adopted in supply-chain management [13], production scheduling [14], parts/vehicle tracking, and so on.

### Wireless Sensor Networks

Wireless sensor networks (WSNs) are composed of spatially distributed autonomous nodes that can sense the environment, conduct computations, and communicate with other nodes [9]. The sensor nodes operate in a self-organized, decentralized manner that maintains the best connectivity as long as possible and sends their data via multihop spreading to the base station. They have to cooperate and use collaborative signal- and information-processing techniques to fulfill their tasks since a single node is not always capable of sensing the whole environment. However, individual nodes are tiny, energy-constrained devices with weak processors and a small amount of memory, which exerts significant influence on the design and implementation of WSNs. WSNs have a wide prospect of applications in various scenarios of sensing-based manufacturing decision making, with obvious advantages such as flexible deployment and configuration and convenient wireless integration.

RFID and WSNs represent two complementary technologies [15]. RFID can be used to discover and identify objects that are not easily detectable or distinguishable using traditional sensor technologies but not to monitor the condition of objects [16]. Comparatively, WSNs can not only provide information about the condition of the objects and environment but also support multihop wireless communication. Some WSNs may be equipped with actuators to perform appropriate physical actions. Ultimately, RFID and WSNs can be combined [16].

### Cloud Computing and Big Data

Based on virtualization technology and service-oriented architecture (SOA), cloud computing enables the efficient management of an extremely large shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction [17]. It has essential characteristics, such as on-demand access, resource pooling (multitenant), rapid elasticity, and measured service (a pay-as-you-go business model). Cloud computing can provide an important thrust toward transforming the manufacturing sector [18]. Cloud manufacturing—a new service-oriented manufacturing paradigm [19]—is one significant effort that has attracted wide global attention [18].

With huge amounts of computing resources, the cloud computing paradigm provides unprecedented capability for the convenient handling of big data generated from IoT-enabled manufacturing. The success or failure of the IoT hinges on big data, which is a broad term for data sets so large or complex that traditional data-processing technologies are inadequate [53]. It has three distinct V characteristics compared to traditional data sets: volume (i.e., large amounts of data, easily accounting for terabytes of data), variety (i.e., the heterogeneity of data types, structured and unstructured data of text, video, images, and so on), and velocity (i.e., the speed of data creation and time frame of data processing to maximize the value) [20], though others later proposed a fourth V (value) and a fifth V (veracity). The lifecycle of big data comprises phases of data acquisition, extraction, integration, analysis, and interpretation [21]. With powerful storage and computing capability, cloud computing plays a fundamental role in the phases of big data's lifecycle. The demands from big data also accelerate the development of cloud computing. In manufacturing, big data can be applied in the full lifecycle of products, significantly impacting design innovation, manufacturing intelligence, cost reduction, quality, efficiency, and customer satisfaction [22], e.g., designing more precisely targeted products and making effective promotion strategies based on acquired knowledge from big data analysis.

Therefore, we can see that the IoT's core technologies have great potential in reshaping the manufacturing sector with pervasive real-time sensing, actuation, and powerful data-processing capabilities. To unlock the IoT's potential in manufacturing, several issues need to be addressed.

## Research Issues of IoT-Enabled Manufacturing

### Reference Architectures and Standards

According to different perspectives, the conceptual architecture can be Internet-centric or thing-centric [23]. Gubbi et al. [23] proposed a cloud-centric framework of the IoT, which includes three layers: a network of things, cloud computing, and applications. The cloud integrates ubiquitous devices by providing scalable storage, computation time, and other tools to build new IoT businesses. The European Union project for IoT architecture [24] is attempting to build a general thing-centric framework that can be tailored according to domain demands.

To organize huge amounts of heterogeneous devices that provide and consume information available on the network and cooperate level, the SOA approach is usually adopted [3], [4], [25] in both Internet- and cloud-centric frameworks. Each real-world device or system can offer its functionality as services. Then various sophisticated services can be created via orchestrating those services. The cloud computing paradigm has allowed the possibility for everything to be provided as services in the long run, which is a concept called *XaaS* [26].

To facilitate the interoperability, virtualization technology is widely used and researched, such as the virtualization of computing, storage, and network resources in the area of cloud computing. Cloud manufacturing tries to apply virtualization technology in the organization of various manufacturing resources and capabilities. He and Xu [18] concluded that the generic architecture of cloud manufacturing consists of five layers: physical resource, virtual resource, core service, application interface, and application. Even though the IoT is claimed to be included in cloud manufacturing, such architecture is actually cloud-centric.

From a data-handling perspective, Lee et al. [5] proposed a five-"C" architecture for cyberphysical manufacturing systems. The architecture comprises a smart connection level to enable data acquisition through the networking of sensors and machines, a data-to-information conversion level to infer meaningful information from data, a cyberlevel to act as central information hub, a cognitive level to generate a thorough knowledge of the monitored system, and a configurable level to make machines in physical space self-configurable and self-adaptive when there is some feedback delivered from cyberspace.

More recent work by Ning et al. [27] brought forward a broader vision of the IoT, where physical perceptions, cyberinteractions, social correlations, and even cognitive thinking can be intertwined in the ubiquitous things' interconnections. Thus, the proposed hyperspace architecture includes cyber, physical, social, and thinking space. Social space refers to the logic architecture of social attributes and interactions owned by human beings and other physical objects, or cyberentities. Thinking space addresses thought- and idea-related issues.

From the organizational aspect, we consider that the manufacturing of the IoT holistically consists of five levels (as shown in Figure 1): sensor–actor–machine, shop floor, factory, enterprise, and supply chain. The IoT can greatly enhance efficient information flow (or even accelerate logistics) downward and upward between any two levels (e.g., cross-layer interaction), leading to a trend of increasingly flatter organizational structures. For example, the geographically distributed IoT-enabled factories can now be efficiently managed and scheduled directly by a single management system, while the need to deploy a great amount of hierarchical and fully functional local management systems is lowered as the IoT pushes more work to be automated and fewer people are involved.

Furthermore, such an efficient organization of resources with the help of the IoT can better support the full life cycle of products (research and development and design, production, marketing and sales, after-sales service). With a powerful IoT infrastructure, any two stages can interact to gain useful feedback rather than having traditional interaction just between two consecutive stages. We are currently experiencing the transition from the seller's market to the buyer's market. Thus, such cross-stage feedback can potentially benefit all value-chain parties. For example, the designers will receive useful user reviews by directly posting their conceptual design to the social network; customers may recommend a customized product that suits their personality.

Another new IoT-enabled paradigm is intelligent products [28] (shown as "in-use product" in Figure 1) that can enforce the online monitoring of product conditions and perform remote diagnosis. This is not covered by the traditional supply chain, which involves the transformation of materials to finished products, even though some used products may reenter the chain again. Based on the acquired online usage data, manufacturers can conduct proactive maintenance or use such information to improve their designs or manufacturing processes. In such a scenario, when the prediction based on real-time data indicates that certain parts should be replaced after some time, orders can automatically be placed so that just-in-time production and the replacement of parts can be enabled to facilitate lean production and reduce costly downtime (improving user experience greatly).

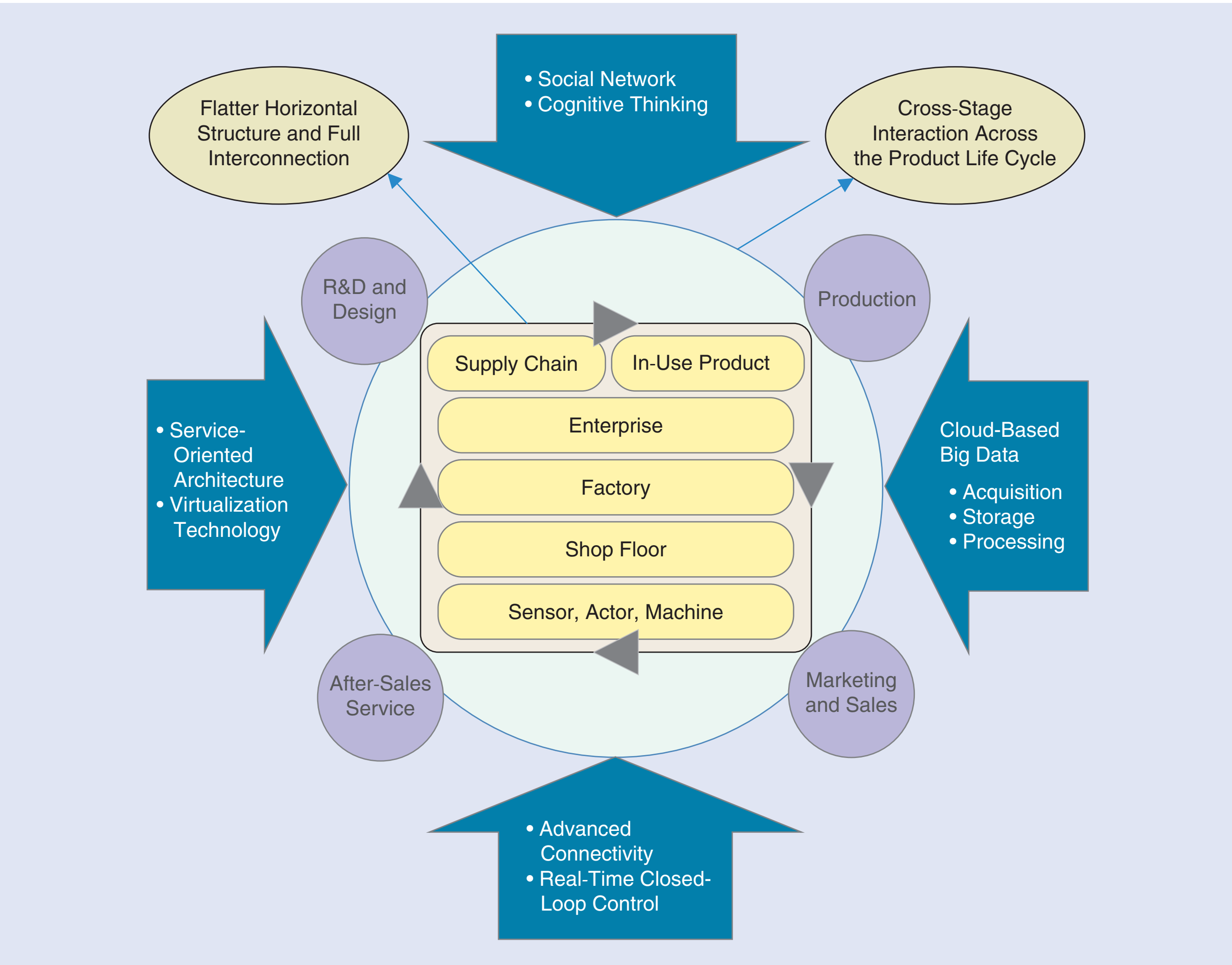


**Figure 1.** The impact of the IoT on the manufacturing industry. R&D: research and development.

Standards are another crucial element to enable intercompany networking and integration through value networks in future IoT-based manufacturing. First, a global standard for the unique identity of each manufacturing object is needed, e.g., IPv6, an IoT enabler with an almost unlimited number of globally reachable addresses. Then, data exchange standards should be designed to facilitate seamless data exchanges between objects, systems, and organizations (e.g., MTconnect [29]) and across the stages of the manufacturing and business planning processes.

### Deployment and Business Models

Undoubtedly, the IoT is becoming an attractive paradigm that can bring great benefits to the manufacturing industry. However, there are still many challenges involved with its practical implementation. The deployment and business models of IoT devices/systems are always a central issue. To enable pervasive sensing and actuation in real time, large amounts of sensors/actuators need to be deployed. Then, questions such as what kind, how many, and where are likely to arise. While we believe IoT devices will become increasingly cheap, large-scale deployments will still cause a huge expense. A cost–benefit analysis is necessary to determine whether the application warrants the high cost or a reasonable investment plan makes more sense.

There is some literature on the return-on-investment analysis of RFID in supply-chain management [13], [30]. However, much effort is needed to build precise models to predict costs and benefits for various application scenarios, as the deployment and operation of WSNs, RFID, and cloud/big data applications are complex. For example, the applications can be deployed in private clouds, community clouds, public clouds, or hybrid clouds. Small and medium enterprises can choose public clouds to better serve their business targets without huge up-front investments, while big corporations can afford to build private clouds under their absolute control. Also, varying pricing strategies can bring different costs. Moreover, technical plans, costs, and benefits intertwine with each other. To tackle this challenge, at a minimum, the following five questions should be answered, taking WSNs applications as an example:

1) What is the immediate problem without WSNs?
2) How can the costs and benefits of deploying WSNs be balanced?
3) Where and how many sensors should be deployed?
4) What process should be used to deploy WSNs (a one- or multistep process)?
5) What is the update and maintenance plan?

For strictly privately owned IoT facilities, enterprises need to cover the whole expense. In other cases, IoT facilities can be shared among companies to improve the utilization rate and reduce the cost, e.g., the sharing of physical assets and service in industrial parks [31]. Designing a feasible business model so that multiple sides can obtain their benefits through information and resource sharing plays an important role in the successful implementation of the IoT infrastructure. This needs to be explored through modeling and analysis, e.g., using game-theory-based methods to model the investment, rules, and revenues. Proper pricing mechanisms should be built to accommodate different use cases and maximize mutual benefits. Duan et al. [32] analyzed and compared different incentive mechanisms for a client to motivate the collaboration of smartphone users on both data acquisition and distributed computing applications. Similarly, incentive mechanisms should be designed for IoT operators and service consumers, based on business models.

### Manufacturing Big Data

The wide adoption of smart-manufacturing devices gives rise to huge volumes of heterogeneous data that are generated and collected. The storage and processing of those manufacturing big data are usually conducted in the cloud. Real-time data from in-use products can elicit an unbounded development of novel online manufacturing applications, like intelligent prognostics. For RFID systems, readers can identify the information contained in tags and store it directly to a (cloud) database. However, data collection in WSNs is much more complex and challenging.

First, proper strategies are needed to balance the on-device/in-network data processing and the cloud-based data processing. The former method can be energy efficient for WSNs, but this may cause the discarding of some useful raw data. Measuring the effectiveness of sensor data is difficult and probably varies on a case-by-case basis. To decide whether the local data should be processed on the base node or uploaded to the cloud is still a challenge. Some applications require a very fast (even real-time) response, e.g., the detection of errors in computer numerical control machines and production systems. In such cases, local data processing is more suitable to enable fast feedback control. The cloud is strong at scalable storage and the powerful processing of big data, but some preprocessing is still required on the base node to prevent the network congestion caused by the transmission of large data sets. An alternative method is to gradually transfer local data sets to the cloud during idle time. A flexible method of collaborative data processing between local nodes and the cloud is needed.

Second, heterogeneous big data (e.g., structured data with different schema and sampling frequency, unstructured or semistructured data) are gathered from various devices. How to correlate big data from different sources and organize those related big data that may be incomplete and/or inconsistent should be explored to lay a solid foundation for the upper-level applications. Machine-learning algorithms expect data that are carefully structured, so adding structures to unstructured data before processing them on a massive scale is the norm [26]. General approaches that provide flexible schema-based big data manufacturing are required to handle multisource data after the preprocessing. The real challenge also lies in how to responsively find enough useful data in manufacturing big data generated from multiple sources. One feasible way is context awareness computing, which stores context information linked to sensor data to decide what data to use and facilitate autonomous machine-to-machine communications [33]. When current big data are not enough, the challenges become how to identify what data are further needed and how to adjust manufacturing the IoT in a low-cost and fast way, which are not easy to resolve. Thus, during data handling, proper metrics or rules should be established to evaluate whether current data sets are enough and what additional data are needed if the current results are not satisfactory. This may also involve the incremental deployment of IoT facilities. Timeliness is another challenge when some applications require instant and responsive big data processing to maximize the benefit gained from big data [21]. The stream-based big data processing, which aims to deliver data analysis results as soon as possible through processing the freshest data sets, is noteworthy in this aspect.

Finally, how to efficiently and flexibly share big data among different data owners and, at the same time, protect the privacy of the owners is challenging. When big data are manufactured, they are usually stored and processed in the cloud. More efforts should be made from both legislative and technical points of view to prevent unauthorized access to private data. Fine-grained and reconfigurable data-sharing mechanisms should be provided to facilitate efficient and secure data sharing. The sharing mechanism of big data may also intertwine with the business models that data owners use to make profits.

### Cyberphysical Models and Simulations

Modeling and simulation are a particularly useful means when the intended system costs too much to be built, physical experiments are dangerous or expensive, or it takes a long time to know the results of the system due to the changing parameters. There are many such scenarios in IoT-enabled manufacturing that require the research and application of modeling and simulation theory and technology to facilitate training, decision-making, and so on.

To hide heterogeneity and facilitate management, physical objects are virtualized and represented as twin models (avatars), and they are seamlessly and closely integrated in both the physical and cyber spaces [2]. Twin models abstract the functions of physical objects [3]. Physical objects and twin models interact in a mutually beneficial manner [34]. The simulation systems that comprise twin models and other digital models will operate as an essential part of the corresponding system. Real-time input data enabled by the IoT can be used to verify and adapt models or drive model executions (i.e., simulation). Simulation results obtained from model executions can guide the IoT-enabled control and actuation of physical objects/systems. Such a smooth bidirectional connection forms a closed loop that can make the state of physical objects converge quickly toward the target state. This can also greatly reduce the cycle time for a model update, analysis, and verification and carry out prompt what-if analyses to respond to abrupt changes [34]. Moreover, the models can act as a filter to ensure the reliability and robustness of high-level decision-making models rather than feeding (incomplete and/or inconsistent) sensory signals directly from the sensing IoT infrastructure [35].

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Basic models that either do or do not interface with physical objects can be combined or composed hierarchically to support higher-level decision-making models for manufacturing and logistic applications in workshops, factories, or organizations. One big challenge is to generate simulation results no later than the required time for the physical objects. Multiresolution modeling and high-performance computing with specially designed/general purpose acceleration hardware (e.g., graphics processing units and many/multiple-core processors) can be used to hasten simulations [36]. Other challenges include the online evolution of models without bringing interruptions to the physical systems according to dynamic environments and the pervasive involvement of users in decision-making activities [36].

There are essentially two kinds of models: mechanism and nonmechanism (such as models established by using machine-learning approaches). Increasingly, nonmechanism models (e.g., deep neural networks) have gained wide attention and have considerable characteristics such as good flexibility, adaptability, and self-learning ability. Big data can be used to build prediction, classification, and cognitive models for optimal decision making on various levels of manufacturing systems and across the full lifecycle of products, such as demand forecasting.

### Open and Intelligent Product

*Open* first refers to the potential involvement of vast human resources in the world. A recent trend is that more people beyond the boundaries of organizations will collectively participate in an activity of the product design and manufacturing. Crowdsourcing [37] and socialized manufacturing [27] are such efforts to tap into the competences of vast human resources outside of the organizations. In such cases, *open product* refers to a class of products that are developed by the crowd in an open way. The trend is also promoted by the boom of social networks, such as Facebook and WeChat, which can provide good communication and sharing spaces. With the emergence of virtual communities of like-minded people, playing different roles (customers, manufacturers, professionals, and more) offers excellent chances to solicit contributions/collaborations from different individuals/organizations with various competences and thoughts. The challenge is to choose the scope and scale of dynamic cooperation and control the quality of contributions. If too many people are involved, not only may high-quality contributions be overwhelmed by massive trivial and unimportant ones, but also the cost may increase significantly or not enough contributions can be acquired. Thus, new metrics, methods, and online supporting tools (possibly domain specific) to address such challenges are necessary.

A typical case is customized or personalized products, which can best meet individual customers' needs. More companies are heading toward providing customized or personalized products to survive in the fragmented, diversified, and competitive marketplace. The challenges lie in defining the functions of a simple graphical-aided software tool for consumers and third parties and the just-in-time production of modules by different parties and the efficient assembling of modules. Quality control (including safety, reliability, and performance, among others) and warranties are also important issues for customized or personalized products [38]. Other challenges come from aspects of production variability and financial viability [39]. We recently proposed a framework to support design and production of customized/personalized products under IoT-enabled manufacturing clouds [40].

*Open product* also means that a product can work and collaborate with other (new) devices or software on an unanticipatedly wide scale. This requires commonly accepted standards and platforms to enable interoperability. In the ecosystem of IoT-enabled workshops, renovated or new facilities need to efficiently cooperate with current machines to automate the production. However, unexpected collaborations can pose great challenges. Mostly, a product is designed to work in specific contexts (i.e., has its own assumptions and control strategy without much knowledge of other products/systems [7]); thus, it usually cannot deal with such openness when renovated or new products are involved. Some of those products can even mutually interfere when functioning. This demands, in part, that the products are intelligent and autonomous (i.e., an intelligent product that contains sensing, memory, data processing, reasoning, and communication at various intelligence levels) [28], such as intelligent agents [41], [52]. Open will also cause grand challenges in the dimensions of security and privacy, as we will briefly discuss later.

### Services Provision and Composition

XaaS is now prevalent in the cloud. It is important to integrate various manufacturing resources and capabilities as cloud services and improve interoperability between services and efficiency of service collaboration during a stage or across multiple stages of the whole product life cycle, especially for users who need multiple services to fulfill an individual complex task [42].

Another perspective is to leverage abundant services from multiple industrial clouds and address the uncertainty issue under today's highly dynamic business environments. We have proposed a hybrid framework for integrating multiple manufacturing clouds [43] in which clouds can form federations to use their aggregated resources and users can have a wider selection of services. Due to the relatively long execution time of manufacturing services, various disruptions can occur and cause a deviation from the target. Thus, the dynamic adjustment of service execution plans is needed to guarantee optimal performance. In this process, the IoT can capture and report the critical events in a real-time manner and thus make the control of service execution a closed loop. We recently developed a framework [44] that uses the IoT's real-time sensing ability on service execution, big data's knowledge extraction ability on services, and event-driven dynamic service-selection optimization to deal with disturbances and continuously adjust the service selection to be more effective and efficient. Proper formulation of the dynamic service selection for varying uncertainties should be built [45].

### User-Centric Pervasive Environment

The IoT has been developed to respond in an intelligent way to the presence of users, thereby providing better support to them in carrying out specific tasks. In manufacturing, this means IoT objects/systems/environments should have the ability to automatically perceive user needs through context awareness so that users can quickly acquire the needed services and focus on their tasks. Compared to closed environments in ambient intelligence, the IoT needs to deal with open scenarios, whereby new functions/capabilities should be accommodated at runtime and may not be considered at the design time [4]. The IoT systems that involve humans also exacerbate this challenge, as human behaviors are driven by a huge range of factors and tend to be much more complex and volatile. This further requires IoT systems to be truly autonomous and intelligent and equipped with a self-learning ability to handle new scenarios properly.

After the perception of user needs, it is necessary to present available services and big data analytics in an easily understood and user-friendly method. Visualization can be of great help; however, it is not easy to visualize unstructured data in a flexible way. Furthermore, the visualization system should be interactive so that users can choose what they want to see and use. To support this, intelligent machines need to autonomously interact with each other behind the scenes to acquire and infer context information. Some wearable or embedded sensors may be used to get users' exact requirements, e.g., to detect their health conditions and predict their behaviors. Such autonomous interaction may be continuous so as to adapt the working environment according to the changing user needs.

Three-dimensional reconstruction and interaction represent a future trend that can provide vivid and immersive experience [46]. In an idealistic scenario, factory workers can talk with reconstructed images of their managers anywhere and anytime, and it would be just like they are talking in the same physical location. Emotional factors are also important for human–machine interactions and virtual/augmented-reality-based remote human–human interactions [47]. In the long term, sense and emotion will be combined to construct an advanced virtual collaboration environment, where users can feel that humans and/or machines work at the same physical site. The humans and machines of interest are pervasively presented around users.

### Other Critical Issues

In manufacturing, there is a large number of latency-sensitive applications that request real-time perception, decision making, and actuation. This requires the collaboration of end devices (e.g., WSNs, mobile phones), mediate nodes (e.g., the base station in WSNs, gateways), and data centers. For the (powerful) mediate nodes, the paradigm has a name, *fog computing* or *edge computing* [48], that complements and extends the cloud computing paradigm to the edge of the network, with characteristics such as low latency, location awareness, and strong presence of streaming and real-time applications. It uses field-area networks at the edge to facilitate the machine-to-machine or human-to-machine interactions. Additionally, it filters data to be consumed locally and sends the rest to the higher tiers.

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Privacy and security issues are crucial in a future open and highly connective world. We have conducted a comprehensive literature review, which is presented in [49].

## Future Applications of the IoT in Manufacturing

### Automation and Production Efficiency

IoT systems collect real-time status data from the factory floors (e.g., machinery, vehicles, materials, people, and environments) and feed them into enterprise decision-making systems. Those data can be used to automate workflows/processes to maintain and optimize design and production systems without human intervention. For example, through process mining powered by the IoT, production processes can be redesigned to achieve high efficiency. With real-time information collected, intelligent algorithms, and networked actuators, the control software can automatically make decisions and drive actuators to shrink the deviations from the plan. Large amounts of multisource data and intelligent machine-learning algorithms can automatically generate optimal decisions. The advance of machine-learning technology substantially increases the level of autonomy to control production processes and deal with various disruptions.

### Energy Management and Green Manufacturing

Manufacturing accounts for about one-third of global energy demand [50]. When coupled with increasing energy prices, energy management is not a trivial issue. Traditional methods are based on isolated plant states without a full understanding of the whole plant due to a lack of infrastructure for holistic mapping to business and fine-grained, continuous measurement of energy consumption. Not only can the IoT help to continuously track and correlate energy consumption and business activities in real time by deploying sensors at any locations of interest; it also enforces online dynamic energy-aware control in the IoT-enabled closed loops.

Energy efficiency should go beyond simple stand-alone approaches, e.g., single process/machine optimization, toward a more holistic view. Cross-domain collaboration (in the physical world, e.g., machinery, materials, and vehicles, and in the business world, e.g., enterprise information systems, production processes, and logistics) and data acquisition and correlation must be in place to develop good strategies. Also, statistical analysis and real-time energy-related indexes should be combined as a whole. Big data analytics can play an important role in moving in the direction of green manufacturing.

### Proactive Maintenance

Manufacturers have widely accepted the concept of proactive maintenance, which advocates early diagnostics and part replacement based on the prediction and monitoring of machine degradation to reduce costly, unscheduled downtime and unexpected breakdowns [51]. Lower-cost sensors, wireless connectivity, and big data tools can deliver useful data and analysis about a machine's status and performance. Historical and real-time data can be modeled, correlated, analyzed, and visualized to make machine degradation predictable and visible. Also, such data can be fed back to product designers for closed-loop life cycle redesign. Proactive maintenance can also be applied to the maintenance of manufacturers' own products to enhance after-sales services.

### Connected Supply-Chain Management

IoT-enabled systems can connect all parties in the supply chain via real-time information sharing on shop floors, inventory, purchasing and sales, maintenance, logistics, and more so that all parties can understand interdependencies, monitor the flow of materials/parts and production cycle time, identify potential issues before they happen, and establish correct measures. This can exert high impact on effective implementation of just-in-time or lean manufacturing. Demand, supply, and feedback information can be accessed by all parties in real time, which will eliminate the information asymmetry problem.

## Conclusion

The IoT is widely accepted as a novel paradigm that can radically transform the manufacturing industry. It can realize the seamless integration of various manufacturing devices equipped with sensing, identification, processing, communication, actuation, and networking capabilities. Based on such a highly integrated smart cyberphysical space, it opens the door to create whole new business and market opportunities for manufacturing. Even though we cannot predict exactly when or whether the IoT will be built globally like the Internet, we can expect it to develop, first, locally and then gradually and possibly become globally unified in the end. IoT-enabled manufacturing (e.g., Industry 4.0, Factory of the Future, and Made in China 2025) is such an effort, which can have a high impact on the global economy.

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