Applications of Internet of Things in Manufacturing

Conference Paper · May 2016

DOI: 10.1109/CSCWD.2016.7566069

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***Abstract*— The Internet of Things (IoT) envisions the seamless interconnection of the physical world and the cyber space. This provides a promising opportunity to build powerful services and applications for manufacturing. This paper provides an overview of key research issues to be addressed and the latest advances in the area of IoT-enabled manufacturing. We first introduce the core technologies of IoT, such as Radio Frequency Identification, Wireless Sensor Networks, Cloud computing, and Big Data. Then we discuss some key research issues of IoT-enabled manufacturing in term of architecture, deployment and business model, data acquisition and processing, model-based decision-making, dynamic service composition, user-centric pervasive environment and latency reduction with state-of-the-art reviews. Finally, we point out some potential application areas of IoT in manufacturing.**

Keywords— Internet of Things; Manufacturing; RFID; WSNs; Big Data; Cloud Computing

I. Introduction

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, lead-time, etc. and growing pressure to meet higher environmental standards due to the "enhanced producer responsibility" [1]. Meanwhile, consumers have more diversified and demanding needs, e.g., customized products. These challenges push the manufacturing industry to embrace new technologies to keep competitive and meet user demands. The Internet of Things (IoT), which has great potential in transforming the manufacturing sector [2], attracts tremendous attention from both academia and industry.

IoT envisions the seamless interconnection of the physical world and the cyber space, and the pervasive presence of them around us [3][4]. The embedding of tiny electronics into physical objects and the networking of them, make them "intelligent" and seamlessly integrated within the resulting cyber-physical infrastructure. Thus IoT can bring the greatly enhanced horizontal integration of various manufacturing resources used in different stages of manufacturing processes, and vertical integration of them at different hierarchical system levels [5][6]. This provides unprecedented opportunities for existing or whole new manufacturing services and applications to leverage such advanced interconnection. For example, the connectivity between smart machines, production facilities, etc. will enable them to autonomously exchange information, trigger actions and control each other independently [6].

Furthermore, the pervasive sensing ability of IoT systems gives rise to the generation of huge 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 at early stages of development and much more IoT devices will be deployed [7]. As an essential part, cloud computing and its supported big data technology play a fundamental role in managing huge amounts of manufacturing resources and providing highly elastic and scalable services to users, such as the powerful capabilities for storing, processing and visualizing manufacturing big data (BD). The results from BD analytics allow manufacturers to better capture business opportunities, to readily adapt to change and to deal with uncertainty promptly.

This paper provides an overview of key challenging issues in IoT-enabled manufacturing (for security and privacy, please see [8]), and discusses some potential applications. Please note that the research issues discussed are rather than complete. The rest of the paper is organized as follows: Section II presents a technical background of IoT; Section III discusses challenging research issues; Section IV identifies future application areas; and Section V provides brief concluding remarks.

II. Background and Enabling Technologies

There are three core technologies that play vital roles in IoT and can benefit the manufacturing industry tremendously.

A. Radio-Frequency Identification (RFID)

RFID uses electromagnetic fields to transfer data, for automated identification and tracking of tags attached to objects [9]. RFID systems consist of RFID tags and readers. RFID tags attached on the objects hold information about the objects, while RFID readers can read such information (including the unique IDs) without requiring a line of sight and report that 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, production scheduling, and so on.

B. Wireless Sensor Networks

The Wireless Sensor Networks (WSNs) are composed of spatially-distributed autonomous nodes that can sense the environment, conduct computations, and communicate with other nodes [10]. The sensor nodes operate in a self-organized, decentralized manner that maintains the best connectivity as long as possible and sends their data via multi-hop spreading to the base station. They have to cooperate and use collaborative signal and information processing techniques in order 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. The nodes may also contain actuators to control the physical characteristics of the world. WSNs have their wide prospect applications in various scenarios of sensing-based manufacturing decision-making.

RFID and WSNs represent two complementary technologies [11]. RFID can be used to detect and identify objects that are not easily detectable or distinguishable by using traditional sensor technologies, but not to monitor the condition of objects. Comparatively, WSNs can not only monitor the condition of the objects and environment, but also support multi-hop wireless communication.

C. *Cloud Computing and Big Data*

Based on virtualization technology and the Service Oriented Architecture (SOA), Cloud Computing (CC) enables efficient management of an extremely large shared pool of configurable computing resources (e.g., networks, servers and storage) that can be rapidly provisioned and released with minimal management effort or service provider interaction [12]. It has essential characteristics, such as on-demand access, resource pooling (multi-tenant), rapid elasticity, and measured service (pay-as-you-go business model). CC can provide important thrust on transforming the manufacturing sector [13]. The proposition of Cloud Manufacturing (CMfg) - a new service oriented manufacturing paradigm [13] is one significant effort, which has attracted wide attention in the world [14].

With huge amounts of computing resources, the CC paradigm provides unprecedented capability for the convenient handling of BD generated from manufacturing IoT. The success or failure of IoT hinges on BD. BD is a broad term for datasets so large or complex that traditional data processing technologies are inadequate. It has three distinct "V" characteristics comparing with traditional data sets: volume (large amounts of data, easily accounting for terabytes of data); variety (heterogeneity of data types, structured and unstructured data of text, video, images, etc.); and velocity (speed of data creation and time frame of data processing to maximize the value) [15], though others later proposed 4th V (value) and 5th V (veracity). The lifecycle of BD comprises phases of data acquisition, extraction, integration, analysis and interpretation [16]. CC plays a fundamental role in those phases of activities with powerful storage and computing capability. The demands from BD also accelerate the development of CC. In manufacturing, BD can be applied in the full lifecycle of products, significantly impacting design innovation, cost reduction, quality, efficiency and customer satisfaction [17], e.g. designing more precisely targeted products and making effective promotion strategies based on acquired knowledge from BD analysis.

Therefore, we can see that IoT's core technologies have their great potentials in re-shaping the manufacturing sector. In order to unlock the IoT's potentials in manufacturing, several issues need to be addressed. We will discuss these issues in the following sections based on the literature survey.

III. RESEARCH ISSUES OF IOT-ENABLED MANUFACTURING

A. *Reference Architecture*

According to different perspectives, the conceptual architecture can be 'Internet' centric or 'Thing' centric [18]. Gubbi et al. [18] proposed a cloud-centric framework of IoT, which includes three layers: 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 EU project of IoT architecture [19] tries 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, the SOA approach is usually adopted [3][4][20]. Each real-world device or system can offer its functionality as services. Then various sophisticated services can be created via orchestrating those services. On the other hand, affected by the CC paradigm, everything can possibly be provided as services in the long run, named "XaaS" [21].

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 CC. CMfg tries to apply virtualization technology in organization of various manufacturing resources and capabilities. He and Xu [14] concluded that the generic architecture of CMfg consists of five layers: physical resource layer, virtual resource layer, core service layer, application interface layer and application layer. Even though IoT is claimed to be included in CMfg, such CMfg architecture is actually "cloud" centric.

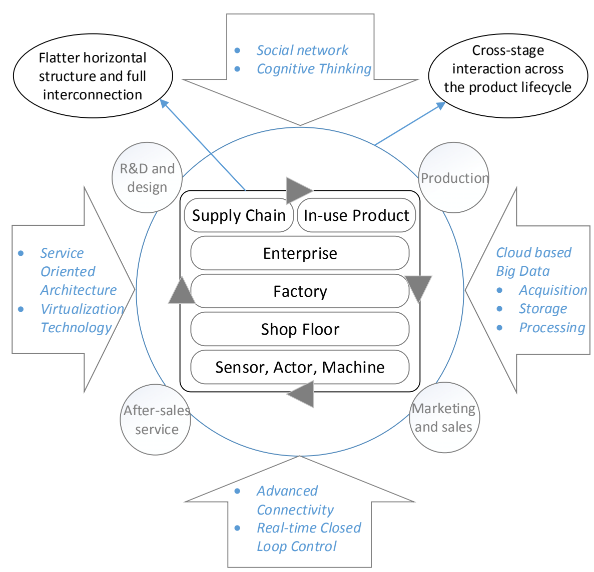

Figure 1. Impact of IoT on the manufacturing industry

Lee et al. [5] proposed a five-layer architecture for cyber-physical manufacturing systems. The architecture comprises: data acquisition level through networking of sensors and machines; data-to-information conversion level; cyber level to act as central information hub; cognitive level to generate a thorough knowledge of the monitored system; configurable level to make physical machines configurable and adaptive.

A more recent work by Ning et al. [22] brought forward a broader vision of the IoT, where physical perceptions, cyber interactions, social correlations, and even cognitive thinking can be intertwined in the ubiquitous things' interconnections. Cognitive thinking relates to thoughts and ideas.

From the organizational aspect, we consider that the manufacturing IoT holistically consists of five levels (as shown in Fig. 1): sensor-actor-machine level, shop floor level, factory level, enterprise level, and supply chain level. 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.

Furthermore, such efficient organization of IoT-enabled resources can better support the full life cycle of products (mainly R&D and design, production, marketing and sales, after-sales service). With a powerful IoT infrastructure, any two stages can interact to gain useful feedback, instead of 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 get 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 [23] (shown as "In-use Product" in Fig. 1) which can enforce the on-line monitoring of product conditions and do 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 re-enter the chain again. Based on the acquired on-line usage data, manufacturers can conduct proactive maintenance or use such information to improve their design or manufacturing process.

B. Deployment and Business Model

Undoubtedly, IoT is becoming an attractive paradigm, which can bring great benefits to the manufacturing industry. However, there are still many challenges toward practically implementing it. The deployment and business models of IoT 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 the IoT devices will become cheaper and cheaper, large-scale deployment will still cost much in advance. The cost-benefit analysis is necessary to determine whether it deserves to do so or make a reasonable investment plan. There is some literature on return-of-investment analysis of RFID in supply chain management, such as [24]. However, much effort is needed to build precise models to predict the cost and benefit for various application scenarios, as the deployment and operation of WSNs, RFID and cloud/BD applications are more 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, the technical plan, cost and benefit intertwine with each other. To tackle this, at least the following five questions should be answered, taking WSNs applications as an example:

(1) what is the immediate problem without WSNs?
(2) how to balance costs and benefits of deploying WSNs?
(3) where to deploy sensors and how many of them?
(4) what process to deploy WSNs (one- or multi-step)?
(5) what is the update and maintenance plan?

For strictly private-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, for example the sharing of physical assets and service in industrial parks [26]. How to design a feasible business model, so that multiple sides can gain their best 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, for example 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. [27] 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.

C. Manufacturing Big Data

The wide adoption of smart manufacturing devices gives rise to huge volumes of data generated and collected. For RFID systems, RFID readers can identify the information contained in RFID tags and store them directly to the database. However, for WSNs, data acquisition involves more steps and complex cooperation, leading to several challenges.

First, dynamic reconfiguration of WSNs and adaptive scheduling of constrained WSNs resources should be studied to effectively accommodate multi-tasks or multi-purposes, as WSNs are increasingly evolving towards open, ubiquitous, interoperable, multi-purpose infrastructures [28]. The context awareness [29] is an important clue to further improve energy-efficiency and high performance of multi-purpose WSNs. Some sensor nodes can move or die, while new nodes may be added. The resulting WSNs should have the ability to reconfigure itself, in order to gain optimal performance [30].

Second, 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. To measure the effectiveness of sensor data is hard and probably 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 very fast (even real-time) response, e.g., the detection of errors in production systems. In such case, the local processing of data is more suitable to enable fast feedback control. The cloud is strong at scalable storage and powerful processing of BD, but some pre-processing is still needed on the base node to prevent the network congestion caused by the transmission of large data sets. An alternative method is to update local data sets gradually during idle time to the cloud. Flexible collaborative processing of data between local nodes and the cloud is needed.

Third, facing heterogeneous data gathered from various manufacturing devices, how to correlate BD from different sources and organize them which may be incomplete and/or inconsistent should be explored to lay a solid foundation for the upper applications. Machine analysis algorithms expect data that are carefully structured, so adding structure to unstructured data is a norm before the massive processing of them [16]. General approaches are required to flexibly handle multi-source data after the preprocessing. During the data handling, proper metrics should be established to evaluate whether current data sets are enough and what's more are needed if the current results are not satisfactory. This may also involve incremental deployment of IoT facilities. Timeliness is another challenge when some applications do require the very fast and responsive processing of BD to maximize the benefits gained from BD [16]. The stream-based BD processing approaches are noteworthy in this aspect.

Fourth, how to efficiently and flexibly share BD among different data owners and at the same time protect the privacy of the owners are challenging. Manufacturing BD is usually stored and processed in the cloud. More efforts should be made from both a legislative and technical point 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 BD may also intertwine with the business models which BD owners use to make profits.

D. *Cyber-Physical Models and Simulation*

To hide heterogeneity and facilitate management, physical objects are virtualized and represented as twin models (Avatars) seamlessly and closely integrated in both the physical and cyber spaces [2][31][32]. Twin models abstract functions of physical objects [3]. Physical objects and twin models interact in a mutually beneficial manner [33]. The simulation system which comprises twin models will operate as an essential part of the corresponding physical system. Real-time input data enabled by 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 seamless dual-way connection forms a closed-loop which can make the state of physical objects converge fast towards the target state. This can also greatly reduce the cycle time for model update, analysis and verification, and carry out prompt "what-if" analyses to respond to abrupt changes [33]. Moreover, the models can act as a filter to ensure the reliability and robustness of high-level decision making models rather than feeding (incomplete or/and inconsistent) sensory signals direct from the sensing IoT infrastructure [34]. Basic models which interface with physical objects or not can be combined or composed hierarchically to support more complex decision-making for manufacturing and logistic applications in workshops, factories or organizations. One big challenge is to generate simulation results no later than the required time of physical objects. Multi-resolution modeling and high performance computing with specially-designed/general-purpose acceleration hardware (e.g., GPU and many-core processor) can be used to accelerate simulations.

There are roughly two kinds of models: mechanism model and non-mechanism model (like models established by using machine learning approaches). Increasingly, non-mechanism model (e.g., deep neural networks) gains wide attention and has very good characteristics like good flexibility, adaptability, self-learning and generalization ability. BD can be used to build prediction, classification, cognitive models for optimal decision-making in manufacturing, such as demand forecasting.

F. *Services Provision and Composition*

Various physical manufacturing resources can be integrated into the cloud and provided as services. "XaaS" is now prevalent in the cloud, but how to improve interoperability between services and efficiency of service collaboration during a stage or across multiple stages of the full product lifecycle is crucial to users who need multiple services to fulfill an individual complex task. Physical resources can be virtualized into logic units which can be flexibly combined in different granularities and provided as services to consumers [35].

Another perspective is how to leverage abundant services from multiple industrial clouds and to address the uncertainty issue under today's highly-dynamic business environments. We have proposed a hybrid framework for integrating multiple manufacturing clouds [36], 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 [31] can occur and cause the deviation from the target. Thus dynamic adjustment of service execution plans is needed to guarantee optimal performance. In this process, IoT can capture and report the critical events in a real-time manner and thus make the control of service execution a close loop. We conducted a preliminary investigation and proposed a framework [37], which uses IoT's real-time sensing ability on service execution, BD's knowledge extraction ability on services in CMfg, and event-driven dynamic service-selection optimization to deal with disturbances from users and service market and to continuously adjust the service selection to be more effective and efficient. Proper formulation of the dynamic service selection for varying uncertainties should be built.

G. *User-centric Pervasive Environment*

The development of IoT is to respond in an intelligent way to the presence of users, thereby to better support them in carrying out specific tasks. In manufacturing, this means IoT facilities should have the ability to automatically perceive user needs through context-awareness, so that users can fast acquire the needed services and focus on their tasks. Comparing to "closed" environments in ambient intelligence, 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 human also exacerbate this challenge, as human behaviors driven by a huge range of factors tend to be much more complex and volatile. This further requires the IoT systems to be truly autonomous and intelligent, like intelligent agents [25] having self-learning ability to handle new cases properly.

After the perception of user needs, it is necessary to present available services and BD in an easy understanding and user-friendly way. Visualization can be of great help. However, it is not easy to visualize the unstructured data in a flexible way. More often than not, the visualization system should be interactive, so that users can choose what they want to see and the customized way of using it. This is the obvious interaction. Behind this, intelligent machines autonomously interact with each other to give support by acquiring and inferring context information. Some body or even embedded sensors may be needed to exactly get user requirements, for example identifying their states (e.g. health indicators) and predicting future behaviors. Such interaction may be continuous to adapt the working environment according to the changing user needs.

The 3D reconstruction and interaction is a future trend that can provide vivid and immersive experience [38]. In an idealistic scenario, factory workers can talk with reconstructed images of their managers anywhere and anytime just like they are talking in the same physical location. Emotional factors are also important for human-machine interactions and virtual-reality based remote human-human interactions [39]. In the long term, sense and emotion will be combined together to construct an advanced virtual collaboration environment, where users can feel that human and/or machines work at the same physical site. The human and machines interested are pervasively presented around users.

H. Other Critical Issues

In manufacturing, there are a large number of latency sensitive applications that request real-time perception, decision-making, and actuation, as partly pointed out above in III.C. This needs the collaboration of end devices (e.g. WSNs, mobile phones), mediate nodes (e.g. base station in WSNs, gateway), and CC centers. For the (powerful) mediate nodes, the paradigm has a name "fog computing" [40], that complements and extends the CC paradigm to the edge of the network, which implies 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. It filters the data to be consumed locally, and sends the rest to the higher tiers. The higher the tier, the wider the geographical coverage, and the longer the time scale and data storage time. Ultimately, it extends to the CC center.

IV. Future Manufacturing Applications of IoT

A. Automation and Efficiency

IoT collects real-time status data from the factory floors (e.g., machinery, vehicles, materials, and environments). Those data can be used to automate workflows/processes to maintain and optimize design and production systems without human intervention. 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 amount of multi-source data and intelligent algorithms (e.g., machine learning algorithms) can automatically generate optimal decisions. The advance of machine learning technology substantially increases the level of autonomy, to control the production processes and deal with various disruptions.

The management (control) of massive IoT devices that are interacting with each other, requests multi-stakeholder involvement and data access that has to go beyond the classical monolithic one-domain and task-specific development approaches. Other challenges include degree of centralization, optional independence of each other of the participating systems, and independent evolution of them.

B. Energy Management

Manufacturing accounts for approximately one third of global energy demand [41], along with increasing energy prices, making energy management a non-trivial issue. Traditional methods are based on isolated plant states without full understanding of the whole plant, due to no infrastructure for holistic mapping to business and fine-grained, continuous measurement of energy consumption. IoT can help not only continuously track and correlate energy consumption and business activities in real time by deploying sensors at any location of interest, but also enforce on-line 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, in a more holistic view. Cross-domain collaboration (physical world, e.g., machinery, materials and vehicles; business world, e.g., enterprise information systems, production processes and logistics), data acquisition and correlation must be in place to make good strategies. Also, statistical analysis and real-time energy-related indexes should be combined as a whole.

C. 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, in order to reduce costly, unscheduled downtime and unexpected breakdowns [42]. Lower cost sensors, wireless connectivity and BD tools can deliver useful data and analysis about the machine's status and performance. Historical and real-time data can be modeled, correlated, analyzed and visualized to makes machine degradation predictable and visible. Also such data can be fed back to the product designer for closed loop lifecycle re-design [31].

D. Connected Supply Chain Management

IoT-enabled systems can connect all parties on the supply chain via real-time information sharing on shop floors, inventory, purchasing and sales, maintenance, logistics, etc., so that all parties can understand interdependencies, the flow of materials/parts and production cycle time, identify potential issues before they happen and make right measures (forming a closed control loop). This can exert high impact on effective implementation of lean manufacturing. Demand, supply and feedback information can be accessed by all parties in real time, which will eliminate the information asymmetry problem. The main challenges include common standards to ensure data exchange, privacy and security of data, and business models of shared information and IoT infrastructure.

V. CONCLUDING REMARKS

IoT is widely accepted as a novel paradigm that can radically transform the manufacturing industry. It can realize the seamless integration of manufacturing devices equipped with sensing, identification, processing, communication, and actuation capabilities. Based on such highly-integrated smart cyber-physical space, it opens the door to create whole new business and market opportunities for manufacturing. IoT-enabled Manufacturing (e.g., German industry 4.0, factory of the future in EU, and Made in China 2025) is such an effort, which can have a high impact on the global economy.

This paper identifies several key common issues of IoT's applications in manufacturing, and provides reviews with some latest advances. Then the potential manufacturing applications of IoT are discussed, along with some challenging domain-specific problems.

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