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Big Data Driven Edge-Cloud Collaboration Architecture for Cloud Manufacturing: A Software Defined Perspective

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ABSTRACT In the practice of cloud manufacturing, there still exist some major challenges, including: 1) cloud based big data analytics and decision-making cannot meet the requirements of many latency-sensitive applications on shop floors; 2) existing manufacturing systems lack enough reconfigurability, openness and evolvability to deal with shop-floor disturbances and market changes; and 3) big data from shop-floors and the Internet has not been effectively utilized to guide the optimization and upgrade of manufacturing systems. This paper proposes an open evolutionary architecture of the intelligent cloud manufacturing system with collaborative edge and cloud processing. Hierarchical gateways connecting and managing shop-floor *things* at the ''edge'' side are introduced to support latency-sensitive applications for real-time responses. Big data processed both at the gateways and in the cloud will be used to guide continuous improvement and evolution of edge-cloud systems for better performance. As software tools are becoming dominant as the ''brain'' of manufacturing control and decision-making, this paper also proposes a new mode - ''AI-Mfg-Ops'' (AI enabled Manufacturing Operations) with a supporting software defined framework, which can promote fast operation and upgrading of cloud manufacturing systems with smart monitoring-analysis-planning-execution in a closed loop. This research can contribute to the rapid response and efficient operation of cloud manufacturing systems.

INDEX TERMS Cloud manufacturing, big data, edge-cloud collaboration, software-defined architecture, Internet of Things.

I. INTRODUCTION

With the development of tiny sensors towards smaller-size, lower-cost, lower power consumption and higher-precision, efforts have been made in developing and applying a large variety of smart sensors, devices and facilities in the manufacturing industry to build what is termed as smart factories. Those smart objects or assets with embedded identification (ID), sensing, and actuation capabilities are usually connected using the Internet of Things (IoT) [1] and 5G technologies [2], and seamlessly integrated into smart manufacturing platforms, like Cloud Manufacturing (CMfg) systems [3] and Industrial IoT [4]. While companies reported on substantial tangible and intangible benefits, they have accumulated a great deal of data collected on a real-time basis from shop-floors or markets, social networks, etc. This calls for better utilization of such big data for the manufacturing industry to gain further benefits through business analytics and artificial intelligence. On the other hand, CMfg as a new service oriented manufacturing paradigm enables the efficient management of an extremely large shared pool of configurable equipment, networking and computing resources (e.g., networks, servers, storage, and services) that can be rapidly provisioned and released [3], and thus can provide highly elastic and powerful capability to handle manufacturing big data. Furthermore, after some knowledge or insights are

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mined from big data, appropriate approaches to rapidly take corresponding actions should be explored to increase the productivity or reduce losses.

However, there still exist some major challenges in the practice of CMfg [3] or industrial IoT [1], [4]:

1) Acquiring real-time data about the factory is a must for data analytics and taking actions. To make the shop-floor transparent and visualized, tiny electronics (sensors in particular) are being embedded into machines and materials and networked, leading to a generation of huge and diverse volumes of data. Uploading Zettabytes of future raw manufacturing shop-floor data (without proper data cleaning and combination at different levels) to the remote cloud can cause serious network congestion and hamper the overall network services quality,

2) Powerful cloud storage and computing capability can support big data analytics and optimal decision-making for manufacturing applications with multi-dimensional big data. However, data communication (between devices and the cloud), synchronization and computation would take a lot of time, which could not meet the requirements of time-sensitive applications on the shop floor,

3) Big data from the shop-floor devices and the Internet has not been effectively utilized to guide the continuous optimization and upgrade of the manufacturing system, or at least the collaboration and evolution of components in edge-cloud based manufacturing systems.

Specifically, product quality, energy conservation, highly customized and personalized needs, and right time windows for highly volatile global markets define the competitiveness of manufacturers. As shown in Fig. 1, these require the big data collected to be mined to reveal knowledge and insights on: (1) Disturbances: How to intelligently respond to various disturbances? (2) Energy intensive operations: How to extract energy consumption patterns for energy saving processing? (3) Unbalanced assembly lines: How to make effective schedules in highly dynamic environment? (4) Defective products: How to identify and control influencing parameters to improve product quality?

4) As for taking actions according to big data analytics enriched decision-making, the manufacturing system lacks reconfigurability, openness and evolvability in terms of structure and parameters, thus restricting the plug-and-play of new resources and the rapid system reconfiguration and optimization, to effectively cope with internal disturbances and external changes. IoT actuators will make the shop-floor more controllable in real-time, but this is not enough for the cases when the reconfiguration of the system is badly needed for the optimal control. Therefore, the manufacturing system that can be changed rapidly to realize fast responses is needed to deal with shop floor disturbances and market changes.

To address these challenges, the core technologies for smart factories that are robust, adaptive and proactive to handle internal and external disturbances should be explored.

The rest of this paper is organized as follows: after reviewing related work in Section II, Sections III and IV present an open and evolutionary edge-cloud collaboration architecture of intelligent CMfg system (iCMfg) and a new mode - big data analytics-enriched smart operations and upgrading, to improve the capability of CMfg for real-time responses and efficient operation and upgrading. Section V presents a real application use case of the proposed architecture. Section VI discusses related challenges which indicate future research directions. Section VII concludes the paper with remarks on future potential of the proposed approach.

II. RELATED WORK

A. MANUFACTURING IOT

Huang *et al.* [5] reviewed the developments in smart manufacturing from late 1990s since the pioneering work at AutoID Labs at MIT and University of Cambridge. During that time, key efforts were made in developing and applying RFID-enabled manufacturing solutions to fill in the gap of collecting real-time shop-floor data to feed computer-integrated manufacturing systems. RFID and WSN (wireless sensor network) are widely adopted in IoT for object detecting and tracking. RFID enables automated identification and tracking of tags attached to manufacturing objects (indirect tracking of the physical movement of the objects). Smart objects and gateways technologies have been developed mainly with RFID devices to collect real-time data related to manufacturing resources including human, machine and materials [6]. WSNs are used to sense the manufacturing environment and status of objects. Currently, the density of sensing and actuation coverage is still at early stages of development and much more IoT devices will be deployed. Adaptive production planning and scheduling systems have been developed with new decision models to take real-time data into consideration [5]. Yang *et al.* [7] proposed a hyper-connection model of product design and manufacturing for customization and personalization in the IoT-enabled cloud manufacturing environment. More recently, Yang *et al.* [8] provided an overview of key issues in IoT-enabled manufacturing, and discussed some potential applications.

The adoption of IoT with pervasive sensing abilities in manufacturing, transforming the physical entities and operators into ''cyber-ones'', will give rise to the generation of industrial Big Data [9]. However, big data which contains useful information and knowledge and can facilitate and enrich various smart manufacturing decisions, has not been well utilized before [8]. IoT and big data can be used to facilitate optimal selection of dynamic services in the manufacturing clouds [10]. Marjani *et al.* [11] reviewed big IoT data analytics from architecture, opportunities and open challenges. The success or failure of manufacturing IoT depends on Big Data, which is expected to reveal valuable insights for industries.

B. CLOUD BASED MANUFACTURING PLATFORM

Cloud computing plays a fundamental role in handling big data with powerful, on-demand elastic storage, network and computing capability. The potential of cloud

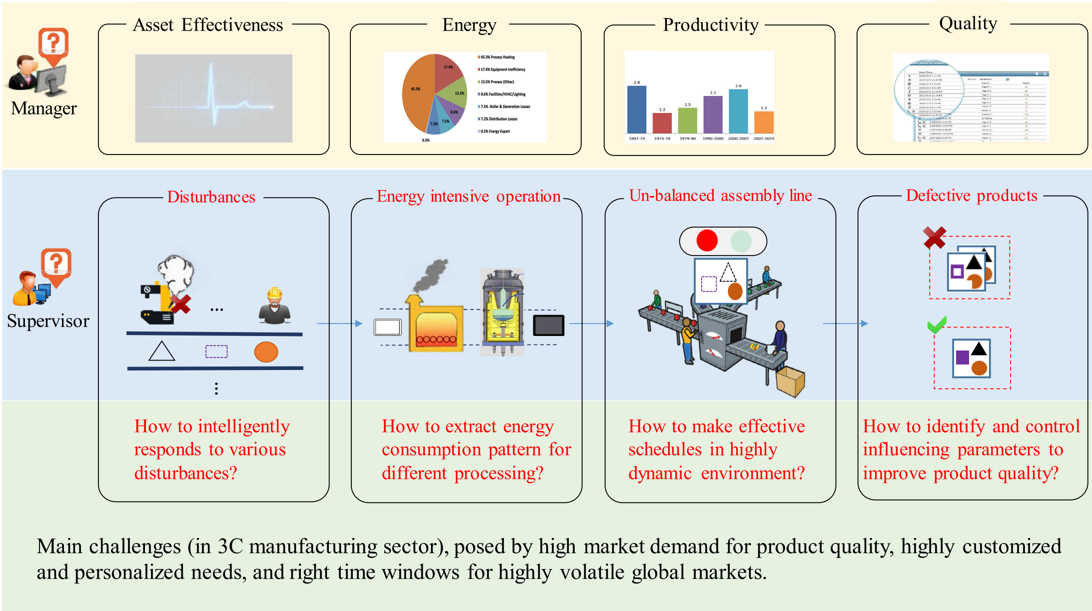

FIGURE 1. Motivating scenarios in Computers, Communication and Consumer electronic (3C) manufacturing.

computing in manufacturing was first explored under the name of CMfg [3]. Wang *et al.* [12] focused on symbiotic human-robot collaborative assembly and sustainable manufacturing adaptive services with cloud architectures for enterprises. Lee *et al.* [13] proposed cyber-physical systems for future maintenance and service innovation under big data environment. Mourtzis *et al.* [14] put forward a cloud-based approach for condition-based preventive maintenance of machine tools, providing a near real-time reporting service on machine remaining operating time, based on shop floor sensor monitoring.

Under the umbrella of CMfg, numerous research results have been published since its first appearance [3]. Early projects in China were exploring the potential of cloud computing in manufacturing [3], [15]. A generic architecture of CMfg consists of five layers: physical resource layer, virtual resource layer, core service layer, application interface layer and application layer [3]. Considering the goals, uncertainties and stakeholders' preferences to incorporate big data analytics in manufacturing systems, a goal-oriented modelling and fuzzy logic-based approach, was proposed to reason and select suitable big data solution architecture [35]. Even though the cloud has powerful computing and storage capabilities for big data analytics, the cloud architecture is not ready to support the reliable real-time or near real-time response of shop-floor applications (such as the control of machine tools and industrial robots) at the "edge" of the manufacturing system, as the data communication between edge *things* and the cloud as well as big data collection, cleaning, combination, synchronization and processing would be time consuming.

Fog/edge computing [16], [17] close to the end *things* can extend, strengthen and complement the CMfg with the capabilities of low latency, location awareness, mobility support and real time analytics. Thus efficient collaborative edge cloud processing approaches in the CMfg should be explored to best deliver various services. More powerful AI chips are being developed in a rapid pace, which can greatly accelerate such process near the "edge". Overall, edge-cloud architecture that supports collaborative optimal utilization of edge and cloud computing resources with the optimal efficiency should be designed to provide various manufacturing services.

C. SOFTWARE DEFINED NETWORK/MANUFACTURING

The primary goal of Software-defined networking (SDN) is to increase the flexibility of networking. SDN allows network administrators to manage network services through abstraction of higher-level functionality [18]. This is achieved by decoupling the system that makes decisions about where traffic is sent (the control plane) from the underlying systems that forward traffic to the selected destination (the data plane). Wan *et al.* [19] proposed a new concept for industrial environments by introducing software defined Industrial IoT, in order to make the network more flexible. Nayak *et al.* [20] proposed a software defined system architecture for dynamically configuring the underlying infrastructure for a manufacturing system. These work would be a good basis for future smart manufacturing. However, gateways (edge) near shop-floor things and edge-cloud collaboration is not considered which can support the evolution of the CMfg system to be more efficient, responsive and robust. Big data and AI should be introduced to a new reconfigurable architecture for better decisions on control plane and data plane.

III. ARCHITECTURE OF SMART CLOUD FACTORY

We propose an open evolutionary architecture of intelligent CMfg system with collaborative edge and cloud processing (Fig. 2) to deal with the above key problems. The vertical dimension shows five layers of SMART infrastructure. The horizontal dimensions show the normal smart factory perspective [5]–[7] (left side) and the aspect of closed loop of system optimization and evolution with collaborative edge and cloud processing (right side).

We will discuss the architecture from the left side - smart cloud factory perspective.

A. PLUG-AND-PLAY CYBER-PHYSICAL MANUFACTURING SYSTEM

The proposed architecture (iCMfg) should support flexible re-configuration of smart devices (objects and assets, such as smart pallets, grippers, fixtures, feeders, and robotic mechanisms) involved in a typical workcell shown in Fig. 2. Sect. IV will present how to achieve this from a software defined perspective. The iCMfg standardizes, synchronizes, and manages devices and events. The iCMfg should be device-independent, scalable, reconfigurable, and with plug-and-play interoperability to connect and accommodate various smart objects/assets.

1) SMART MANUFACTURING ASSETS AND OBJECTS

Various heterogeneous manufacturing resources can be encapsulated into smart objects/assets [5]–[7] to support assembly automation. Two types of smart manufacturing objects will be generated in this encapsulation procedure: active and passive smart manufacturing objects which can execute the manufacturing logic and events automatically. Active smart manufacturing objects carrying RFID readers are able to detect the passive smart manufacturing objects. To improve resource effectiveness and cope with order variety, manufacturing resources should be easily reconfigured within a workcell for new orders adapting to physical and logical relationships.

2) ANALYTICS-ENRICHED SMART GATEWAYS

The aim of the gateways [6], [7] is to facilitate coordination and interoperation among different levels of assets via establishing hybrid management network and protocol convertors, and realize operation synchronization through handling big data collected from assets with high frequency. The gateway is designed to support freely create upward and downward hierarchy to realize multi-dimensional cooperation (three types of smart Gateways for workcell, workshop, and enterprise levels). With built-in data analytic algorithms, models and communication rules, smart gateways are capable of executing tasks (e.g., handling real-time data) and assigning tasks collaboratively. These gateways can be equipped with powerful GPUs or AI chips to conduct very fast pipeline processing of data. This hierarchical or heterarchical gateways with built-in models and coordination mechanisms can be configured dynamically by commands from the cloud big data analytics for better performance. New manufacturing things can be integrated into gateways in a plug-and-play manner. The gateways (edge) can evolve collaboratively with the cloud processing to better provide edge intelligence [21].

The gateways can be 5G base stations connected through the 5G wireless communication technologies. 5G is the fifth-generation wireless technology for digital cellular networks that incorporate new technologies such as SDN/ VNF, millimeter wave communication, massive MIMO, mobile edge computing, etc. [2], [22]. It is predicted that the 5G system should be able to deliver communication services with significantly improved capabilities (10-100 times) in throughput, speed, latency, reliability and security, and to support three main uses: enhanced mobile broadband, massive machine type communications, and ultra-reliable low latency communications [23].

The ubiquitous operation system (UOS) refers to the software system that operates on heterogeneous hardware and virtualizes their functions for unified resource/task management and usage [24]. We use the UOS in iCMfg to denote the software part of the cyber-physical manufacturing system: (1) The UOS can virtualize, connect and manage various manufacturing things so as to achieve a scalable and reconfigurable applications. Manufacturing resources can be added or removed for different orders at hierarchical levels of workcell, workshop and enterprise without affecting each other; (2) Coordination mechanisms and protocols converters can be designed and developed to coordinate, synchronize, and control smart assets and objects; and (3) A Data Analytics Service with suitable models to make full use of the vast sensor data should support real-time synchronization and management. Those models and coordination mechanisms can be reconfigured or upgraded for better performance in iCMfg. For example, a manufacturing cell, an efficient grouping of the resources required to manufacture a product, must be "smart" enough to produce a wide variety of orders of fluctuating volumes, with the UOS support. The UOS will receive the results from the cloud big data analytics and drive the interconnected things and network in an efficient and effective way to cooperate with the iCMfg cloud platform, for example to reconfigure the sensors or machine equipment or network for new product orders.

B. BIG DATA ANALYTICS KERNEL

The comprehensive big data (from multiple dimensions) can be collected from the cyber-physical manufacturing system below by IoT devices or from the internet, such as social networks or e-commerce platforms, and stored in the cloud. Big Data analytics kernel will mine the big data offline to extract information or knowledge for different levels of decision making, for example supporting the efficient edge cloud collaboration towards lean manufacturing. Basic approaches for big data analytics include MapReduce, machine learning,

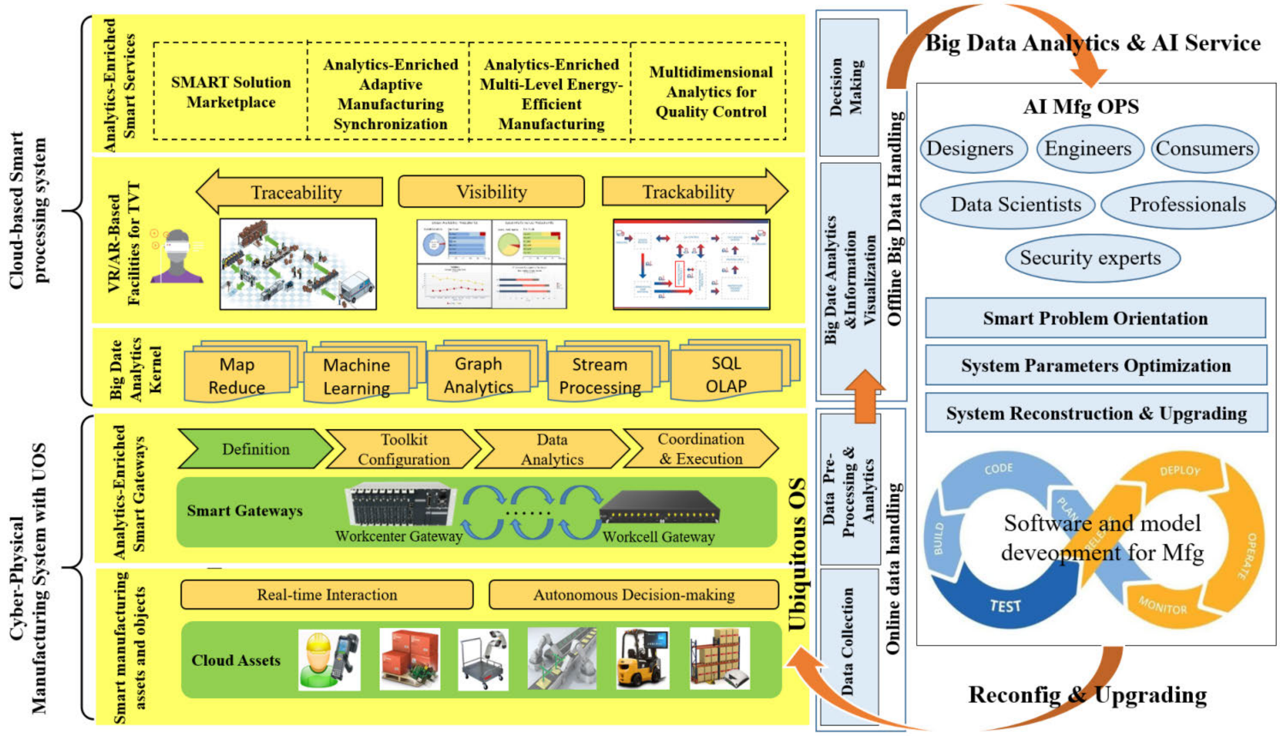

FIGURE 2. Edge-cloud collaborative iCMfg Architecture.

reinforcement learning, graph analytics, stream processing, and SQL online analytical processing [25].

Big data and this kernel service can be utilized to mine knowledge or insights about trends (predictive maintenance), bottlenecks, and how to set the parameters, processing algorithms/rules or coordination mechanisms of gateways and the cloud for data processing.

C. VR/AR-BASED FACILITIES FOR TVT

TVT represents Traceability, Visibility and Trackability. Initial implementations and explorations of smart manufacturing have demonstrated the great potential of data transparencies and traceability within manufacturing environments [26]. Such real-time traceability and visibility can substantially reduce the complexity and uncertainties of manufacturing systems from NP-hard to a level that can be easily addressed locally and globally.

Virtual Reality/Augmented Reality (VR/AR) Facilities for TVT can be dashboards for shop-floor operators and supervisors, and control towers for enterprise-wide and supply chain TVT. Basic VR model can be embedded in visualization and traceability facilities, to vividly present real-time status, trends, statistical information, etc. This VR model can be further enhanced into AR model. Then smart gateways or wearables should be integrated with AR/VR facilities to achieve the interactivity and real-time behaviors for shop-floor workers. AR/VR models can also be fully integrated into iCMfg platform for uses in smart manufacturing services.

D. ANALYTICS-ENRICHED SMART MANUFACTURING SERVICES

Just like e-banking and mobile banking services have reshaped the banking services and businesses, smart manufacturing services deployed in the cloud will gradually change the way that shop-floor operations and decisions are made, executed and monitored. Operators, supervisors and managers of all levels are able to use their mobile and desktop devices to carry out manufacturing decisions related to plans and operations, energy consumption, product and service quality, manufacturing asset maintenance and management. A suite of cloud manufacturing services enriched with business analytics for typical manufacturing decisions and operations should be provided, such as:

(1) Analytics-Enriched Adaptive Manufacturing Synchronization - A radical shift is enabled by real-time visibility and traceability from solely focusing on punctuality of planning and scheduling to simultaneity to maximize the manufacturing performance. **(2) Analytics-Enriched Multi-Level Energy-Efficient Manufacturing** - For energy intensive operations and processes, sensors are deployed to capture energy consumptions. A series of data analytics can be conducted to identify energy consumption patterns for scheduling of energy saving as well as diagnosis of working conditions. **(3) Multidimensional Analytics for Quality Control** - In addition to backward tracing of quality problems and forward tracking of preventive actions, multidimensional real-time data analytics enables to build a model between key quality metrics and process/operational parameters for proactive and precise quality control. When there are defective products found, multidimensional big data analytics can be used to find the failure roots of defective products or to predict the quality in advance. **(4) iCMfg Solution Marketplace** - All hardware devices, desktop services and mobile apps are deployed in the iCMfg market for companies to adopt/adapt according to their specific needs. The marketplace will aggregate the developers and users to form a prosperous manufacturing service ecosystem. The relevant players including cloud vendor, service/apps provider, marketplace operator and end users can get benefits from the ecosystem.

E. COLLABORATIVE THING-EDGE-CLOUD PROCESSING

The cloud with an extremely large pool of configurable storage, networking and computing resources can perform relatively centralized computation intensive tasks, such as long-term global data mining, however, the cloud computing paradigm often cannot meet the stringent requirements of latency, security and privacy sensitive, or geo-distributed industrial applications, due to frequently unpredictable network bandwidth, latency or reliability, especially in a mobile environment. On the other hand, the growing amount of data generated by end devices and systems on the outer edge of pervasive networks often can become impractical or resource prohibitive to transport over networks to remote clouds.

Therefore, decentralized and autonomous decision making on the end *things* or edge computing nodes is an alternative without relying only on persistent and resilient connections to the cloud. However, even in industrial applications, their demands on latency, reliability, mobility, etc., are diverse, therefore, proper allocation mechanisms and algorithms of computing, storage, and caching tasks between the cloud and the edge nodes should be explored. The edge caching can be of great help to distribute large amounts of data from the cloud center to the edge nodes, to reduce latency and to alleviate traffic redundancy and in-network burden [27]. The offloading of computation intensive and data intensive tasks from the manufacturing things with constraint resources to the edge nodes or from the edge nodes to the cloud is an efficient approach to meeting the low latency demand of innovative manufacturing applications [28]. The SDN that decouples the control plane from the data plane can increase the flexibility of networking [29]. The SDN allows network administrators to manage network services through programming at the control plane, to realize the monitoring-analysis-planning-execution closed control loop for industrial communication requiring different QoS [29]. The machine-edge-cloud collaborations requires five types of communications as shown in Fig. 3 (cloud-edge, edge-machine, edge-edge, SDN-edge, machine-machine) to promote the efficient collaboration on computing, communication and storage tasks.

Overall, the architecture can 1) realize autonomous real-time shop floor data collection and coordination in a plug-and-play manner, gaining intelligent decisions through local data and big data analytics, and establishing a cloud marketplace for picking customized solutions with great

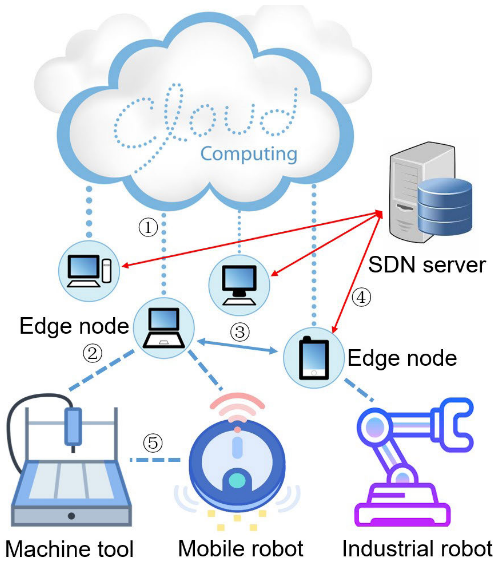

FIGURE 3. Device-Edge-Cloud Collaborative Processing.

accessibility and flexibility; 2) create a new approach for developing the dashboard with ability to find backward reasons of problems, display real-time status, and predict future risks through virtual reality technology; 3) monitor and control quality issues, energy intensive operations and manufacturing planning and scheduling via interactive big data analytics; and 4) provide an edge-cloud collaborative processing approach for different needs of processing speeds and working scope.

IV. BIG DATA ANALYTICS-ENRICHED SMART OPERATIONS AND UPGRADING - AI-CMFG-OPS

This section describes a new dimension of future CMfg or smart manufacturing from a data driven software defined perspective. Big data collected through the cyber-physical manufacturing system can be mined and analyzed to get knowledge or insights for system optimization, operations or evolution, such as to deal with unexpected machine breakdowns, energy intensive operations, low scheduling performance, product defectiveness, fast changing market, etc. Real-time or near real-time online data processing is conducted in the cyber-physical manufacturing system at the "edge" side for fast local response, while the offline big data analytics are performed in the cloud for global and comprehensive view and vision to guide the smart fault localization or predictive maintenance, system parameter optimization, and system reconfiguration and upgrading.

A. SOFTWARE DEFINED CLOUD MANUFACTURING FRAMEWORK

For the purpose of rapid and efficient actions, SDN [18] has been incorporated to make the cyber-physical manufacturing system programmable and controllable via software, in which big data analytics and AI can be integrated to intelligently control the system (e.g., the edge-cloud collaborative

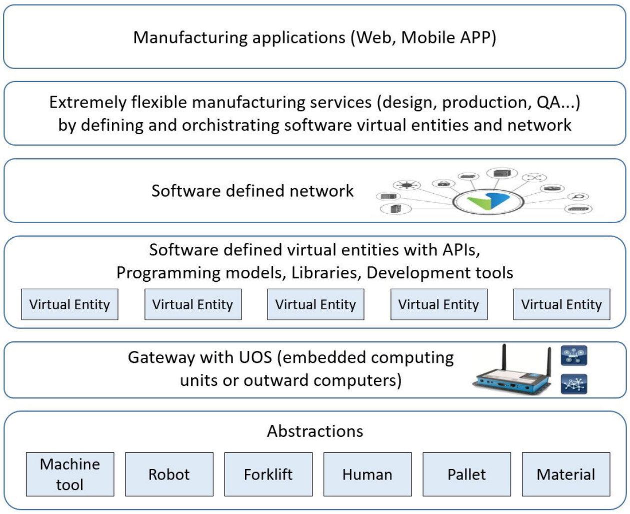

FIGURE 4. A software defined perspective of smart cloud manufacturing.

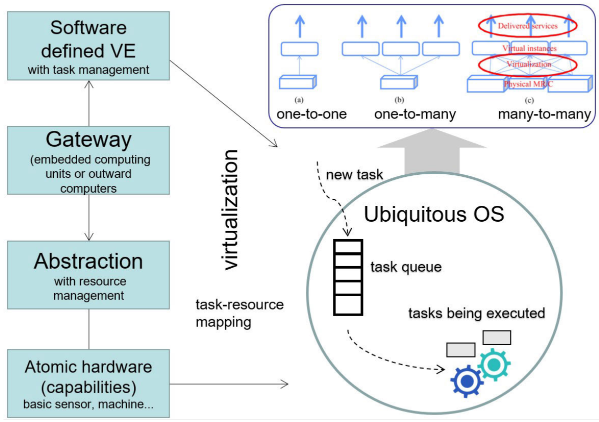

FIGURE 5. Atomic hardware to software defined VE.

processing). Therefore, we propose a software defined cloud manufacturing framework, which can greatly improve the reconfigurability and agility of iCMfg system (Fig. 4). The framework consists of six layers: abstractions, gateways, software defined virtual entities, software defined network, manufacturing services and manufacturing applications. The details are presented as follows.

A concrete basis for big data driven software defined cloud manufacturing is the development of general-purpose reconfigurable executive hardware (maybe open sourced), which can be programmed to provide different functions. We call those basic indispensable executive machines or sensors on the "edge" side atomic hardware. Various virtualization technologies enable the encapsulation and abstraction of heterogeneous atomic hardware through abstraction and gateway, as a software defined virtual entity (SDVE) (Fig. 5) in the cyberspace to provide generic/unified software development kits, like APIs, programming models, libraries, development tools. The abstraction layer manages the atomic hardware resource with basic programmable functions, while the gateway (embedded computing units or independent computers) can support integrating atomic hardware into the cyberspace and act as bridges for bi-directional interactions. The SDVE should be able to manage tasks for the corresponding hardware, as the hardware usually has limited hard resource. The SDVE can be flexibly defined or programmed to provide required functions for different manufacturing tasks. As shown in Fig. 6, the hardware modules (HM) 1 and 2 or HM 2, 3 and 4 can be programmed and organized to provide different functions (a) or (b) for user tasks, i.e. the SDVEs can be defined according to application demands.

Through virtualization, different mapping relationships between hardware resource and SDVEs in the cyberspace (one-to-one, one-to-many and many-to-many, Fig. 5), can be established to support multiple user tasks. For example, a machine tool typically has the one-to-one relationship with its virtual entity, because it usually could not process two or more workpieces at the same time. A high-performance server can be virtualized into multiple virtual machines in the cloud (one-to-many). Cloud computing can efficiently manage the fine-grained hardware like multi-cores on a computer with the latest virtualization technology. A manufacturing capability comprising machines and operators can be divided into different number of virtual instances if measured in man-month or man-hour (many-to-many). Here each virtual instance is established for each user-task. After networking of these hard resources, the Service Oriented Architecture is employed to deliver services of virtual instances for user tasks.

The gateway concerns how to virtualize, wrap up and network manufacturing resource as standard manufacturing services, while the service layer focuses on how to establish composite manufacturing services based on simple services of SDVEs that are registered and published.

On a higher layer to network those SDVEs for complex manufacturing tasks, the SDN is adopted to enable the flexible re-configuration of network to meet the requirements of manufacturing applications (Fig. 6). The SDN can increase the flexibility of networking by clearly separating the basic network functionality of forwarding (data plane) from the network configuration (control plane). The network data plane is implemented "in hardware" by network switches, whereas the network control plane is outsourced to standard hosts implementing the logic to configure the network, e.g., the forwarding tables of switches. Thus, we can flexibly and dynamically control the behavior of the manufacturing system network by implementing application-specific network control logic in software modules ("monitor-analysis-plan-execute" control loop) according to the requirements of the manufacturing applications, for instance, by configuring suitable paths between a dynamic set of sensors and actuators.

As for networking, 5G technologies provide the network characteristics essential for manufacturing, such as low latency and high reliability to support critical applications, high bandwidth and connection density to secure ubiquitous connectivity, and cutting cables to make the manufacturing system truly flexible [23]. Industrial control and factory automation, e.g., the motion, positioning, or torque control of machining tools and robots, call for real-time ultra-reliable data communication, processing and decision-making of 5G systems [30]. A high volume of near real-time data about manufacturing processes collected by 5G communication systems enables the improvement of current analytics and the development of innovative applications.

B. BIG DATA DRIVEN AI-MFG-OPS

A flexible and rapid mode for reconfiguring or updating the manufacturing system can be realized in this framework. We call this new mode as AI-CMfg-OPS (AI enabled CMfg operations). The new AI-CMfg-OPS can shift from the manufacturing system, defined by hardware and logistics constraints to one that is largely defined by software. In this mode, the procedure to get a desired manufacturing service for complex tasks include objective setting, SDVEs and networks selection, SDVE definition and SDN definition. According to the objective (functions, QoS, etc.) and big data about the manufacturing system, suitable networked SDVEs should be optimally selected to collaboratively finish the complex task. Then the selected SDVEs and the networks between them should be configured either manually or automatically by software modules to provide certain executive functions and to better fulfill the task with required communication performance. Through these steps, SDVEs and SDN can be defined and orchestrated to deliver competitive manufacturing services for various users. In other words, the physical resources are virtualized and divided into several logic units or slices [31], [32] for different users.

As the above configuration process can be conveniently realized in software as control logic (''the brain'') of the manufacturing system, we can incorporate the DevOps for continuous build, test, integration, delivery and deployment pipeline (source control, build, staging and production), an agile software development method, to quickly develop, deploy and deliver those software-based controllers of the iCMfg system. A controller can be designed as a collection of loosely coupled small micro-services, which can be independently built, tested and deployed in the DevOps pipeline in seconds/minutes, enabling the rapid, frequent and reliable delivery of large, complex applications.

In the context of SDN, the programmable SDVEs and SDN create excellent opportunities for the software-based control modules which oversee automation hardware and can powerfully and autonomously monitor, interact, react and self-optimize in an extremely fast efficient way without human interventions. This continuous improvement and close loop control of the manufacturing system for better system performance, product quality, lead-time, etc., can greatly enhance the capability and flexibility of the system to cope with the market changes and shop-floor disturbances. In contrast to the agile software development activities most in the digital space, the test/simulation environment of software controllers will involve more physical things than standard computers, and thus should further adopt the digital twin models of

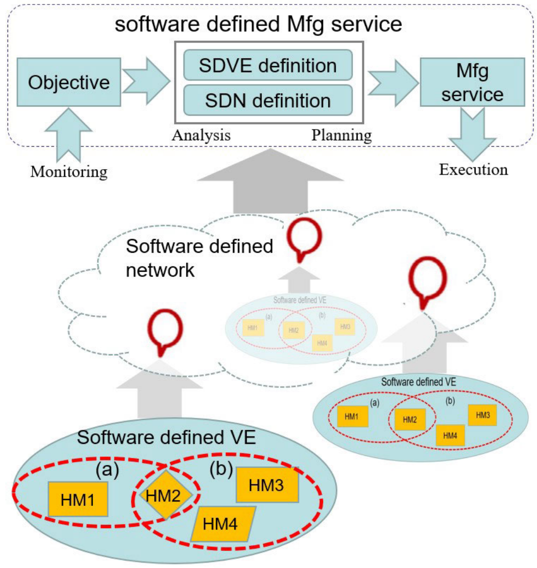

FIGURE 6. Software defined network of software defined manufacturing Virtual Entities.

physical manufacturing entities in the computing environment (virtual machine, or docker container) to make the test results more dependable and verify the control logic. Other simulation models about conceptual objects or future upcoming scenarios, or physical objects representing actual objects can be built to verify the new plan or design.

With this powerful software defined cloud manufacturing framework (versatile reconfigurable and programmable resources/software defined networking/smart applications), the evolution of manufacturing systems can be driven by big data analytics enriched system optimization and upgrading. The close loop (monitor-analysis-plan-execute) can enable the fast convergence of the system towards the optimal. The ultimate goal or most advanced stage of AI-CMfg-Ops is that the manufacturing system can autonomously monitor, react, self-optimize and evolve to become more efficient, robust, intelligent, energy-saving and responsive. Smart production will be a continuous process of constant updates, enhancements, and improvements driven by both business and technology. The human labor will gradually move to highly creative work.

Overall, this framework enables the rapid and flexible optimization and upgrading of the manufacturing system (in terms of parameters and structure), such as the extremely fast distribution and upgrade of software for machineries, devices, computers and networks. The manufacturing capability can be brought to a whole new level to cope with the fierce competition and fast-changing market. This shapes a new powerful manufacturing mode in the ICT-based smart digital world.

V. REAL LANDSCAPE OF TESTBED

The iCMfg will bring immense growth opportunities to enterprises, while simultaneously posing a challenge to each

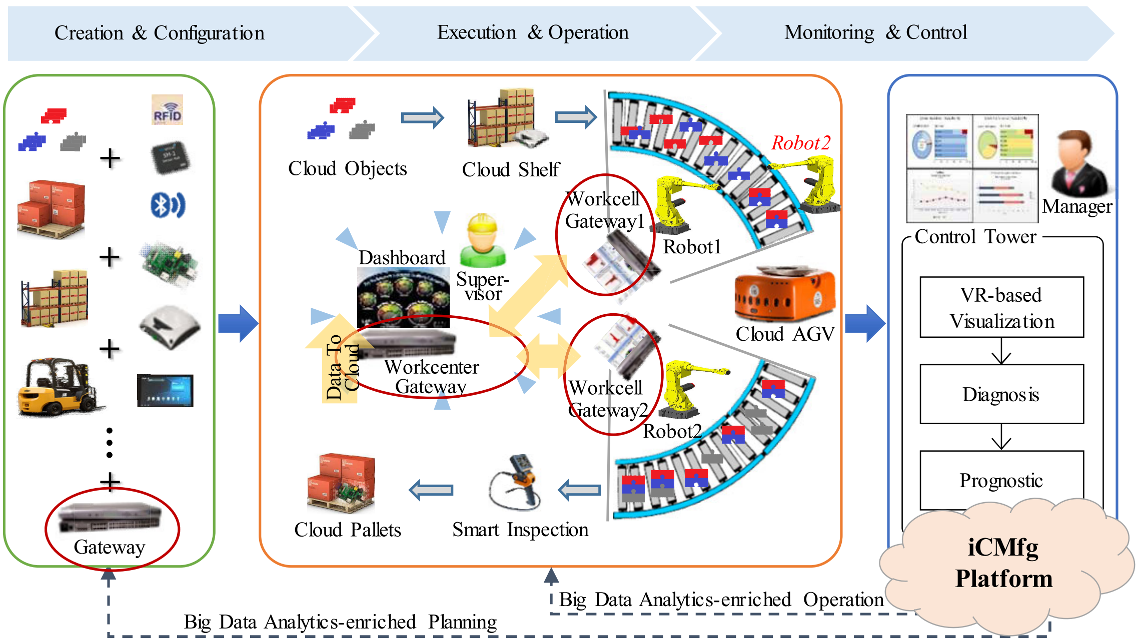

FIGURE 7. Creation & configuration, execution & operation, and monitoring & control of smart factory.

company's very survival. Key technologies built-in iCMfg are sophisticated. Their effectiveness and advantages must be verified for practical dissemination. We design typical industrial settings to demonstrate its practicality and working procedure (See Fig. 7). Within the roadmap of iCMfg, the tasks are conducted following the bottom-up approach by building up the iCMfg infrastructure vertically upwards in Fig. 7. Focused solutions are gradually unfolded from left to right horizontally.

As shown in Fig. 7, the materials, shelves, pallets, trolleys, forklifts are equipped with RFID tags or blue tooth devices or wireless sensors with unique IDs. Gateways can be configured to relay the data or commands, upward to the cloud or downward to the smart objects/assets. Workcell Gateway1 will sense the cloud objects, cloud shelf, assemble robot and cloud AGV, while Workcell Gateway2 will connect cloud AGV, assemble robot, smart inspect tools, and cloud pallets. Gateways can be mobile ones (e.g., with AGV as bases) to suitable shop-floor sites, so that those edge computing nodes can cover most shop-floor areas where the smart objects locate, and perform fast computing tasks to meet smart objects' needs. Workcell Gateway1 and Gateway2 are bi-directionally connected to Workcenter Gateway, which interacts with and uploads the shop-floor data to the iCMfg cloud platform. With those real-time data, the material flows, manufacturing processes and status of the smart objects/assets can be transparent to shop-floor managers or relevant workers to make decisions. Supervisors on the shop floor can see the shop-floor status through site dashboard on top of Workcenter Gateway, and interact with virtual/augmented-reality based wearable devices. The manufacturing big data like object position, process status, machining time, energy consumption, quality data, worker ID, etc., can be collected and mined to get more information for process optimization or reconfiguration. Managers can see the visualized information and knowledge (such failure rates, productivity, energy consumption, asset effectiveness, etc.) to make decisions about the factory operations. If the production workshop should be reconfigured, then the orders can be issued to shop-floor gateways to perform quick adaptations, so that the productivity can be improved by undertaking different tasks in different time intervals. The experimental results will be reported separately due to page limit.

We will take the assembly of cell-phones as an example to demonstrate the iCMfg. The software defined iCMfg system will have extremely high reconfigurability to deal with market changes and internal disturbances. As for the market changes, we are currently experiencing the transition from the seller's market to the buyer's market [8]. Customized/personalized products are gaining more shares in today's product market, which can best meet individual customers' needs and is a future trend [7]. The cell-phone orders from the market consist of personalized and customized cell-phones requiring different manufacturing processes. This will require fast changing and configuration of assembly lines, which are traditionally static with predefined sequences. This requirement in nature also applies to the promise (held by Industry 4.0) of enabling "last-minute changes to production" and delivering the ability to respond flexibly to disruptions and failures [33].

Customer, professionals, product designer, manufacturer (software engineer) and quality inspector will collectively deliver personalized cell-phones. The basic functions of assemble robots and AGVs (such as replacing fixtures of robots, moving to a position) are virtualized, servicized and can be programmed to realize complex tasks. For example, in Fig. 7, software engineers can code manufacturing processes to enable the collaborative assembly of personalized cellphone between Cloud Robot1 and Cloud Robot2, which is different from mass production of standard cellphones. First, Cloud Robot2 is programmed to move to a new position near Cloud Robot1. During such process, positions about Robot2 are reported in real-time manner. Software will control this procedure until Robot2 finally move to the predetermined position. Originally, the two robots (Robot1 and 2) perform the standard cell-phone assembly task sequentially, with AGV to ship parts between them. The network is also programmed to reinforce the communication between Cloud Robot1 and Cloud Robot2, by connecting Cloud Robot2 to Workcell Gateway1 and allocating more bandwidth and switching to establish direct connections between the two with low information delay. In such software defined cloud manufacturing system, Cloud Robot1 and Cloud Robot2 can closely and efficiently cooperate to finish the assemble task of personalized cell-phones. Before deployment to iCMfg system, the codes should be tested in the simulated environment with digital twin models about the shop-floor things to ensure the safety and feasibility. Security mechanisms should also be designed and added in this software defined process, which will be reported separately.

Big Data analytics performed in the iCMfg can greatly enrich decision-making on planning and operations of the shop floor. In an advanced mode, the AI and Big Data driven software will autonomously and intelligently define and evolve the iCMfg system to be more effective and efficient.

We gained primary insights from building such system. Building all-encompassing systems (blindly invest in everything) for smart factories is often very complicated and generally involves long lead-times. We need to avoid technology-dominant initiatives that lack strategic guidance or business value drivers. At the beginning, the most pressing task is to handle business issues as guided by the strategic vision, in accordance with business values, and through the use of innovative technologies. As the unique details of each implementation become clear, it is essential to incorporate the core values of the enterprise and then iteratively progress from general principles to complex details to assure that the strategic vision is included in the completed facility.

VI. CHALLENGES

To achieve this vision of intelligent CMfg, collective efforts should be made by the ICT, robotics, automatic control and manufacturing communities. This data driven edge-cloud collaboration architecture and software defined network mode will become a norm in the future smart connected world, as software is becoming dominant in many intelligent things and systems. On the way to this future vision, there are several challenges ahead.

1) Standards and Interoperability: Standards are another crucial element to enable inter-machine, inter-factory or inter-company networking and integration through value networks in future IoT-based cloud manufacturing [8]. Software defined cloud manufacturing will require a common standard as a foundation to network and integrate manufacturing assets or objects into the cyberspace and to facilitate interoperability at all levels. The digitalization, virtualization and configurability of manufacturing resources is the basis. The future development trend should also be considered in the standards. The traditional manufacturing equipment assumes more or less human participation, but they are seldom designed to be working with no human intervention. This is important for constructing unmanned autonomous intelligent systems. How to integrate and virtualize various heterogeneous/legacy resources is always a challenge in the coming Internet of all manufacturing things. As for interoperability, manufacturing resources must be able to cooperate each other at both physical and information levels on a real-time online basis or an offline basis.
2) Simulation, Verification, Validation and Accreditation (VV&A): As it is easy to develop and deploy software modules to define the manufacturing system, how to guarantee that software can behave as conceived is another challenge. Simulation based on digital twin models and other digital models is an effective approach. Then the VV&A should be addressed to establish its credibility of simulation. During the digital twin simulation, physical objects and digital twin models interact in a mutually beneficial manner, to form a closed control loop [8]. One big challenge is to generate simulation results no later than the required time for the physical objects. 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, for example, interactively using real-time data driven VR/AR facilities for traceability, visibility and trackability.
3) Collaborative Data Processing and Big Data Analytics. Real-time data are generated at different levels and stages of manufacturing environments for different purposes, such as quality control, energy consumption, machine conditions, job progresses, etc. How to aggregate data vertically and horizontally across the manufacturing systems remains a challenge. Data is also collected along the timeline in multi-dimensions for backward evaluation and forward prediction. Data cleaning and aggregation near the end devices can reduce the amount of data transmission in the network, but the challenge is to avoid or at least evaluate information loss in this process. Proper strategies are needed to balance the on-device/at-gateway/in-network data processing and the cloud-based big data processing [8]. The balance between the response speed and the quality of data analytics is another challenge to strike to meet

diverse application demands. This may be a continuous optimization process. A flexible and evolutionary method of collaborative data processing between local nodes and the cloud is needed.

4) Security and Privacy. Privacy and security issues are crucial in a future open and highly connected world. The software defined iCMfg system has high flexibility and openness, while this may also lead to security risks. Cyber-attacks can cause serious problems to the whole manufacturing systems, through hacking virtual entities and networks or inserting malicious codes in the cyberspace. The smart manufacturing entities may also be maliciously organized to launch large Distributed Denial of Service (DDoS) [36] attacks using AI and machine learning. This is a long term and challenging issue. From the data perspective, the blockchain technology emerges as a novel promising solution that can be explored to increase the data security and privacy [34]. A blockchain uses a distributed ledger to store data in interlinked blocks through an entirely decentralized model with consensus mechanisms to validate the transactions and data.

VII. CONCLUSION

This paper proposes to build up a big-data driven evolutionary smart manufacturing architecture with collaborative edge-cloud processing capability. Manufacturing resources including assets and materials are converted into smart cloud assets and objects (with corresponding virtual entities in the cloud) following a Human-Cyber-Physical System approach. Interactions among cloud assets and objects are captured by smart gateways (hierarchical or heterarchical) that are equipped with real-time workflows for business logics, coordination mechanisms for tasks and distributed analytics. Guided by AI-enabled manufacturing big data analytics, the smart gateways and the managed smart cloud assets and objects (''edges'') can evolve together with the iCMfg platform (''cloud'') to be more efficient and robust. Cloud technology adopted in the platform can support various applications with super elastic computing and storage resources. The edge-cloud iCMfg architecture is also strengthened by the software defined framework. Software defined features are introduced to further strengthen the flexibility of iCMfg systems. The smart co-evolution in terms of structures and parameters will form an intelligent monitoring-analysis- planning-execution closed loop and bring a new vision for industry 4.0. This framework equips the iCMfg system with extremely high flexibility and reconfigurability, which is fairly important for the modern manufacturing industry.

Overall, the use of iCMfg will bring a paradigm shift from traditional manufacturing to a new big data analytics enriched smart manufacturing for Industry 4.0, and its key impacts lie in the following four aspects: 1) In terms of technologies, the traditional manufacturing information infrastructure will be shifted to the cloud, which enables a benign and flexible environment for real-time data collection, services integration, and operation synchronization. 2) In terms of decision making, through using hand-held devices like smartphones, it changes the way for operators to collect real-time manufacturing data, interact with each other, and make on-site control during manufacturing processes. 3) For manufacturing companies, big data analytics enables them to better understand the inter-relationships between manufacturing processes and their key performance indicators, including energy consumption and product quality, making it possible to take real-time control for the whole processes and systems. 4) For customers, the visibility of the manufacturing processes and the increased quality of products provide them with improved confidence on the value of products. 5) In terms of ecosystem, big data driven transparent and software defined smart cloud manufacturing system will work in a very efficient and fast-responsive way to all stakeholders like designers, factory workers, owners, and customers, which will cultivate new business models.

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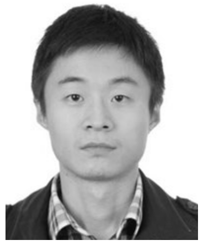

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