From Industry 4.0 to Agriculture 4.0: Current Status, Enabling Technologies, and Research Challenges

Ye Liu , *Member, IEEE*, Xiaoyuan Ma, *Student Member, IEEE*, Lei Shu , *Senior Member, IEEE*, Gerhard Petrus Hancke , *Senior Member, IEEE*, and Adnan M. Abu-Mahfouz , *Senior Member, IEEE*

***Abstract*—The three previous industrial revolutions profoundly transformed agriculture industry from indigenous farming to mechanized farming and recent precision agriculture. Industrial farming paradigm greatly improves productivity, but a number of challenges have gradually emerged, which have exacerbated in recent years. Industry 4.0 is expected to reshape the agriculture industry once again and promote the fourth agricultural revolution. In this article, first, we review the current status of industrial agriculture along with lessons learned from industrialized agricultural production patterns, industrialized agricultural production processes, and the industrialized agri-food supply chain. Furthermore, five emerging technologies, namely the Internet of Things, robotics, artificial intelligence, big data analytics, and blockchain, toward Agriculture 4.0 are discussed. Specifically, we focus on the key applications of these emerging technologies in the agricultural sector and corresponding research challenges. This article aims to open up new research opportunities for readers, particularly industrial practitioners.**

***Index Terms*—Agriculture 4.0, industrial agriculture, Industry 4.0, precision agriculture.**

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Ye Liu is with the College of Engineering, Nanjing Agricultural University, Nanjing 210031, China (e-mail: yeliu@njau.edu.cn).

Xiaoyuan Ma is with the Shanghai Advanced Research Institute, Chinese Academy of Sciences, Shanghai 201210, China, and also with the School of Electronic, Electrical and Communication Engineering, University of Chinese Academy of Sciences, Beijing 100049, China (e-mail: maxy@sari.ac.cn).

Lei Shu is with the College of Engineering, Nanjing Agricultural University, Nanjing 210031, China, and also with the College of Science, University of Lincoln, Brayford Pool, Lincoln LN67TS, U.K. (e-mail: lei.shu@ieee.org).

Gerhard Petrus Hancke is with the Department of Computer Science, City University of Hong Kong, Hong Kong (e-mail: gp.hancke@cityu.edu.hk).

Adnan M. Abu-Mahfouz is with the Council for Scientific and Industrial Research and with the Department of Electrical and Electronic Engineering Science, University of Johannesburg, Johannesburg 2006, South Africa (e-mail: a.abumahfouz@ieee.org).

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I. Introduction

A. Agricultural and Industrial Revolutions

THE ROADMAPS of the agricultural revolution and industrial revolution are depicted in Fig. 1. Traditional farming practices from ancient times, when farmers heavily relied on indigenous tools like hoe, sickle, and pitchfork for cultivation, to the end of the 19th century is referred to as Agriculture 1.0 [1]. Such peasant farming required a great deal of manual labor, but productivity was very low. Taking advantage of the benefits from the first industrial revolution (Industry 1.0) during the period between 1784 and around 1870, agricultural production increased at the beginning of the 20th century referred as Agriculture 2.0, when agricultural machinery was introduced for seedbed preparation, sowing, irrigation, weeding, and harvesting. Mechanized agriculture greatly increased food production and reduced manual labors.

The second industrial revolution took place in the 20th century, referred to as Industry 2.0. On the one hand, the main energy source, which was steam, was replaced by oil and gas. The new energy sources, together with innovations in the transportation industry, greatly contributed to the development of the agri-food supply chain, in which agricultural products could be shipped to long distances. Consequently, new agricultural markets were created for farmers as previously isolated communities were connected together. On the other hand, the introduction of assembly-line-based mass production significantly improved the efficiency and productivity. This mass production model in the manufacturing industry was then applied to livestock production, where traditional home-based animal husbandry was replaced by large-scale intensive animal farming.

Subsequently, the advancement of embedded systems, software engineering, and communication technologies during the era of Industry 3.0 further improved the automation capability of manufacturing equipment. Green renewable energy, such as photovoltaic power, hydroelectricity, and wind power, was also being explored. These above-mentioned developments led to the recent agricultural revolution, known as Agriculture 3.0, which aimed at exploring information technologies for precision agriculture [2] through yield monitoring, variable rate applications, and guidance farming systems.

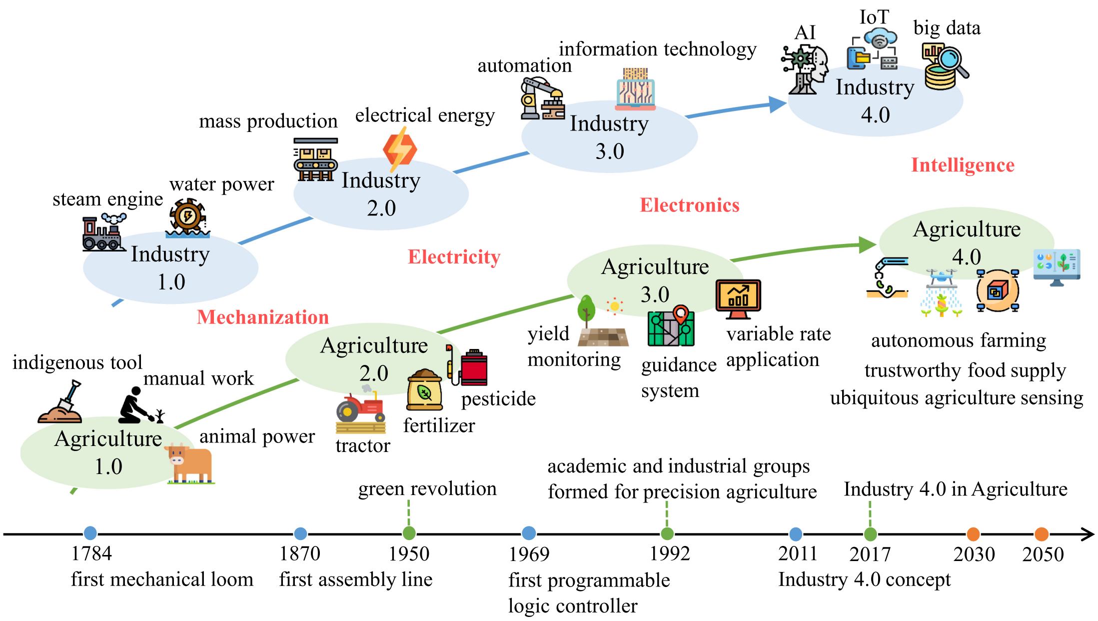

Fig. 1. Development roadmap of industrial revolutions [3] and agricultural revolutions.

In a nutshell, the three previous industrial revolutions gradually modified the form of agricultural activities. The traditional labor-intensive agriculture has been replaced by industrial agriculture through the adoption of industrial production patterns, industrial production processes, and industrial supply chain management in agriculture. Currently, industrialized food production and distribution dominates the global agriculture industry because this method is more productive and cost effective.

B. From Industry 4.0 to Agriculture 4.0

However, there still exist several issues that need to be addressed in the current status of industrial agriculture, such as ecological problems, lack of digitization, food safety issue, and inefficient agri-food supply chain. A more detailed discussion is given in the next section.

The fourth industrial revolution (Industry 4.0) is ongoing, and is characterized by a fusion of emerging technologies such as the Internet of Things (IoT), robotics, big data, artificial intelligence (AI), and blockchain technology. At present, industrial production processes and supply chains have become more autonomous and intelligent. Correspondingly, the integration of Industry 4.0 and agriculture provides the opportunity to transform industrial agriculture into the next generation, namely Agriculture 4.0 [4]. In this context, sustainable and intelligent industrial agriculture would be achieved through real-time variable fine-grained collection, processing, and analyzing spatio-temporal data in all aspects of the agricultural industry, from food production, processing, distribution to consumer experience. Such an industrial agriculture ecosystem with real-time farm management, a high degree of automation, and data-driven intelligent decision-making would greatly improve productivity, agri-food supply chain efficiency, food safety, and the use of natural resources.

C. Related Surveys and Our Contributions

A survey of related work was conducted to compare existing state-of-the-art (SoA) papers with this study, as well as direct readers to more information. Literature was collected across several academic research databases, including the Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. Since this study falls in the area of Industry 4.0 and Agriculture 4.0, the following search keywords were used: "Industry 4.0 + Survey/Review," "Agriculture 4.0 + Survey/Review," and "Industry 4.0 + Agriculture 4.0." To refine the search results, highly cited papers in the field, hot papers in the field, and highly relevant survey reports were selected, which are summarized in Table I.

Generally speaking, several authors [3], [5]–[10] presented comprehensive literature reviews and in-depth discussions on how emerging technologies could be harnessed to transform manufacturing, production, and supply chain management in modern industrial field. Interestingly, the application of Industry 4.0 technologies in fighting coronavirus (COVID-19) pandemic was introduced in [11]. Different from the above-discussed works, the motivation of this article is to provide discussions on the adoption of Industry 4.0 approaches in the agriculture industry. Over the last three years, many high-quality surveys on this topic (i.e., the application of modern technologies in the agriculture industry) [12]–[25] have been conducted, in which the roles of emerging technologies, such as IoT, robotics (drone included), and AI, in smart agriculture are provided. The agriculture industry can be roughly divided into agri-food production and agri-food supply chain management. Different from existing surveys, this article provides readers with the current status and lessons learned from industrial agriculture in terms of industrialized agricultural production pattern, industrialized agricultural production process, and industrialized agri-food supply chain. Moreover, we aim at providing readers with key applications

TABLE I
SUMMARY OF SOA SURVEYS RELATED TO INDUSTRY 4.0 AND AGRICULTURE 4.0

Reference	Year	Target Application Field			Technology Focused					
		Manufacturing	Production	Supply Chain	IoT	Robotics	AI	Big Data	Blockchain	Others
Industry 4.0										
Lu [5]	2017	✓	✓		✓			✓		✓
Qi et al. [6]	2018	✓						✓		✓
Xu et al. [7]	2018	✓			✓					✓
Aceto et al. [3]	2019	✓	✓		✓	✓	✓	✓	✓	✓
Frank et al. [8]	2019	✓	✓	✓	✓			✓		✓
Raut et al. [9]	2020	✓		✓	✓			✓	✓	✓
Oztemel et al. [10]	2020	✓			✓	✓	✓	✓		✓
Javaid et al. [11]	2020				✓	✓	✓	✓		✓
Industry 4.0 in Agriculture (Agriculture 4.0)										
Elijah et al. [12]	2018		✓		✓			✓		
Braun et al. [13]	2018			✓		✓				✓
Kovács et al.. [14]	2018			✓	✓			✓		✓
Belaud et al. [15]	2019			✓				✓		
Zambon et al. [16]	2019			✓						✓
Ayaz et al. [17]	2019		✓		✓	✓				✓
Farooq et al. [18]	2019		✓		✓					
Kim et al. [19]	2019		✓			✓				
Ruan et al. [20]	2019		✓		✓					
Miranda et al. [21]	2019		✓		✓	✓	✓			✓
Zhai et al. [22]	2020		✓				✓			
Ferrag et al. [23]	2020		✓						✓	
Rubio et al. [24]	2020		✓		✓	✓	✓	✓		
Lezoche et al. [25]	2020			✓	✓		✓	✓	✓	
This Study	2020		✓	✓	✓	✓	✓	✓	✓	

TABLE II
TAKE-HOME MESSAGES OF CURRENT STATUS AND LESSONS LEARNED ABOUT INDUSTRIAL AGRICULTURE

	Agricultural Production Pattern	Agricultural Production Process	Agri-food Supply Chain
Current Status	• Monoculture • Intensive Animal Farming	• Mechanization • Informatization	• Business to Business to Consumer (B2B2C) • Online to Offline (O2O) • Customer to Customer (C2C)
Lessons Learned	• Ecological Problems ◦ soil degradation ◦ lost biodiversity ◦ synthetic material overuse ◦ environmental pollution ◦ climate change • Public Health • Animal Welfare	• Lack of Digitization ◦ pre-digital machinery ◦ elementary precision agriculture ◦ basic rural telecom infrastructure • Lack of Intelligence ◦ weak data integration ◦ weak element tracking capability ◦ multi-sources and heterogeneity ◦ secure data sharing • Need of Industrialized Small Farm	• Food Safety Issue ◦ food contamination ◦ low food quality • Asymmetric and Fragmented Information ◦ imbalance supply and demand ◦ price volatility ◦ food scarcity ◦ lack of food traceability • Inefficient Supply Chain ◦ food loss ◦ food waste

and technical challenges for future research when Industry 4.0 meets agriculture.

The rest of this article is organized as follows. Section II presents the current status and lessons learned from industrial agriculture. Subsequently, Section III discusses enabling technologies toward Agriculture 4.0 in terms of key applications and research challenges. Finally, Section IV concludes this article.

II. UNDERSTANDING TODAY'S INDUSTRIAL AGRICULTURE

This section discusses the production pattern, production process, and supply chain in industrial agriculture. More specifically, we focus on its current status and lessons learned. The take-home messages are summarized in Table II.

A. Industrialized Agricultural Production Pattern

1) Current Status: Monoculture and intensive animal farming are the typical characteristics of agricultural production in modern practices. Monoculture is an industrialized pattern of food production, where a single type of cereal, vegetable, and fruit is cultivated on the same farmland year after year. This pattern increases productivity during the entire agricultural cycle, as farmers only need to focus on a single plant species, and creates a uniform plan for seeding, fertilization, irrigation, and harvesting. It is also profitable as a specialized set of farm equipment for one specific crop is sufficient without investing in other types of expensive farm machinery.

Intensive animal farming means that thousands of chickens, pigs, or cattle are raised in indoor facilities at a high density to produce food (e.g., meat, eggs, and milk) more efficiently and economically. This pattern helps feed the increasing urban population with few farmers because it not only increases food production but also promotes the fall of food prices.

2) Lessons Learned: Monoculture farming has shown its advantage of increasing yields and boosting profits over many years of practice, but it also resulted in many ecological problems [26]. Growing a single crop on the same farmland year by year excessively depletes the soil nutrients, which meanwhile cannot be supplemented from surroundings due to the lack of biological diversity in monoculture farming. Nutrient depletion and farmland soil erosion aggravate plant diseases and pests. To protect crop plants, farmers have to use the chemical fertilizers, herbicides, and insecticides, which, in turn, damage farmlands, pollute water, and become a serious threat to human health.

Intensive animal farming also has negative impacts [27] on environmental pollution, climate change, public health, and even animal welfare. Local farmlands are overwhelmed by a million tons of manure produced by a huge number of animals in a concentrated space. Rather than providing nutrients for crop growth, the redundant waste pollutes soil and river. Moreover, industrial livestock production is one major cause of climate change due to the heavy greenhouse gas emissions. Disease-causing organisms, such as bacteria and viruses, are more easily generated in animal factories and spread between the crowded animals, farmworkers, and their communities. Lastly, the unfair treatment of livestock raises the animal ethical issue due to the serious harmful physical and physiological effects on livestock.

B. Industrialized Agricultural Production Process

1) Current Status: The mechanization revolution in agricultural production has ended or is experiencing a rapid transition in most countries. Agricultural machinery and equipment are now widely used during the entire production process, including land preparation, crop planting, fertilization, harvesting, animal feeding, and food processing. Agricultural mechanization significantly reduces manual work and improves productivity, so that fewer farmers can provide more food to meet the high global demand for food. More excitingly, the innovation of information and communication technology and its integration with agricultural production is promoting the digital farming transformation. Sensors are used to measure the status of soil and plant leaves for precise microclimate control [28]. Low-power wide area networks and wireless mesh networks are deployed to report the data generated during agricultural production [29]. Large-scale farmland monitoring, crop identification, and yield forecasting are available through remote sensing [30].

2) Lessons Learned: Compared to the advanced industrial production processes, the automation capability in agricultural production process is limited due to the following two barriers: lack of digitization and lack of intelligence in agriculture.

Most of the agriculture machines in use are still predigital. The analog equipment works independently and is manually operated by humans. To further improve the automation capability, full connectivity of agricultural machinery is vital during the whole production process. Precision agriculture is still in its preliminary stage. Real-time monitoring of farmland, livestock, and other agricultural activities through wireless sensor networks (WSNs) are currently in small scale and short term due to the high deployment and maintenance cost. Further improvement is needed in the network bandwidth and delivery latency to ensure large-scale high-throughput plant phenotyping [31]. In rural areas, the lack of telecommunications infrastructure can only provide limited signal coverage, making it difficult to increase agricultural productivity.

Furthermore, weak data integration and element tracking capability in agricultural information systems hinder multiscale analysis and environment reproduction, and make it difficult to discover biological knowledge. The utilization of big data in agriculture is challenging as agricultural data are collected from individuals, research groups, and companies using different types of devices, which causes multisources and heterogeneity problems [32]. In addition, secure data sharing between multiple groups is an obstacle to the full exploitation of agricultural big data. Consequently, the abovementioned issues need to be addressed from all perspectives on standardization, technological innovation, and legislation.

Last but not least, most of the developed mechanized agricultural machinery and systems are for large farms since large-scale monoculture farming is their main production pattern. However, different kinds of small farms are widely distributed across the world [33], especially in developing countries. In addition, the benefits of small farm are gradually recognized [34], [35]. Distributed small farms would be a possible agricultural production pattern for sustainable agriculture in the era of Industry 4.0. Therefore, the industrialization of small farms should also be paid significant attention [36], [37].

C. Industrialized Agri-Food Supply Chain

1) Current Status: It usually involves five stages from farm to fork, namely food production, industrial processing, distribution, retail, and consumption. A few types of vegetables, fruits, or animals are mass produced on each farm. After the harvesting and selection by farmers, these agricultural food products are sent to rural cooperatives or food brokers for industrial processing, such as sorting, grading, and packaging. The food products are then aggregated to the top wholesalers in each region through transportation and logistics services. Thousands of food retailers, such as supermarkets, farmers' markets, and grocery stores, in the region need to place orders for the food products from the top wholesalers to make food products available for sale. Finally, consumers can purchase their favorite vegetables, fruits, and meats conveniently at retail outlets. This model is commonly referred to as business-to-business-to-consumer (B2B2C) [38].

In recent years, the integration of the Internet and agriculture has promoted new food supply models such as online-to-offline (O2O) [39], social commerce [40], and customer-to-customer (C2C) [41]. These models greatly improve shopping convenience, as prospective customers could search and order preferred food products online. Then, the products could be either picked up from stores or delivered at home.

2) Lessons Learned: The three lessons learned in the agri-food supply chain are food safety issue, asymmetric and fragmented information, and an inefficient supply chain.

First, accidental and deliberate food contamination incidents have occurred too often in the last decades. These incidents usually result from the use of prohibited chemicals, unsafe raw materials, unapproved food additives, as well as insufficient poor storage and poor transportation conditions. Food fraud and low food quality lead to significant negative impacts on public health and consumer confidence. Therefore, ensuring transparency and traceability throughout the entire agri-food supply chain is essential to prevent food fraud, improve the quality of food, and finally boost consumer confidence.

Second, asymmetric information between food production sectors and end consumers leads to an imbalance between supply and demand, price volatility, and foods scarcity. Fragmented information exchange or even data isolation across the agri-food supply chain causes inadequate communication between multiple actors and the lack of food traceability. These, in turn, affect logistics efficiency, cost containment, risk management, customer intimacy, and consumer confidence. Thus, it is urgent to realize a consistent interconnection between all the elements, so that data and discovered knowledge could be efficiently shared among the elements in the agri-food supply chain.

Third, according to the Food and Agriculture Organization of the United Nations, more than 30% of the world's food produced each year is not consumed due to food loss and food waste. Food loss occurs at every stage of the agri-food supply chain, especially during food harvesting, sorting, grading, and processing. This is due to the lack of technology and adequate management, such as a mismatch in supply and demand, poor food quality, and lack of processing techniques, in the existing agri-food supply chain. Meanwhile, food waste usually happens during the later stages in distribution, retailing, and consumption. This is mainly because the food is damaged or spoiled during the logistics process, expires at retailers, or consumers end. Accordingly, it is essential to further improve the technical and managerial capabilities throughout the agri-food supply chain to prevent food loss and waste.

III. Industry 4.0 Technologies in Agriculture

Using emerging Industry 4.0 technologies in agricultural production and agri-food supply chain management provides an opportunity to address the limitations discussed above. Correspondingly, the blueprint of Agriculture 4.0 would also be realized. Five emerging technologies on key applications for Agriculture 4.0 and research challenges are discussed below.

A. Internet of Things (IoT)

1) Key Applications of IoT in Agriculture: The IoT, as a core technology in Industry 4.0, is transforming many aspects of our daily lives by creating a smart connected world. Some use cases are smart home, industrial internet, and connected vehicles. Accordingly, it is also expected to encourage the agricultural sector. The agricultural applications of IoT include precision farming, livestock monitoring, smart greenhouse, fishery management, and weather tracking. As these agricultural applications of IoT were comprehensively reviewed in [12], [17], and [18], we herein discuss them at a general level, namely space–air–ground–undersurface integrated network (SAGUIN) for ubiquitous agriculture sensing and networking.

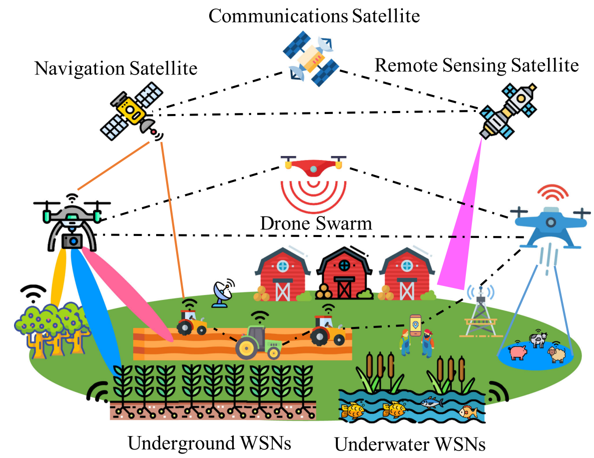

Fig. 2. SAGUIN for ubiquitous agriculture sensing and networking.

The paradigm of SAGUIN is demonstrated in Fig. 2. It would be realized through the combination of remote sensing, drones, smart agricultural vehicles, WSNs, and mobile crowdsensing. Based on national and commercial space infrastructure, the establishment of remote sensing satellite constellation would be able to provide full coverage acquisition of agricultural information, which is especially efficient for crop production forecasting, yield modeling, pest identification, etc. In addition, the advanced unmanned aerial vehicles equipped with hyperspectral sensors, multispectral cameras, and other novel instruments can provide fast emergency responses and improve observation precision through high-throughput 3-D monitoring at different geographical areas. Finally, different kinds of agricultural sensor nodes, autonomous farm vehicles, and mobile crowdsensing are responsible for ground and undersurface perception. Thanks to advances in communication technologies, different types of wireless networks (e.g., 5G, LoRa, NB-IoT, Sigfox, ZigBee, and WiFi) can be chosen to meet the diverse service requirements in agricultural applications (such as real-time remote equipment control, high-throughput plant phenotyping) for better coverage, connection density, bandwidth, and end-to-end latency.

2) Research Challenges of IoT in Agriculture: Several technological issues, however, are faced when applying IoT to agriculture, which are discussed as follows.

a) Professional agricultural sensors: Many issues arise when it comes to environmental sensing in agriculture. Precision agriculture requires a variety of sensors to be deployed on the farm fields, crop plants, animals, and agricultural equipment. However, the lack of professional sensors is a serious obstacle for fine-grained agriculture monitoring, especially in livestock biosensing and plant phenotyping. To address this issue, professional agricultural sensors with high quality, high resolution, and high reliability need to be designed and developed for the perception of agricultural production environments and physiological signs of animals and plants. The study of sensorless agricultural sensing with radio signals could be another direction. For example, WiFi signals can be used to perform accurate measurement for soil moisture and electrical conductivity [42].

b) Wireless power transfer and ambient energy harvesting: Low-power sensing is essential in agricultural environments as a large number of sensors are placed underground, underwater, on trees, and on livestock, making it difficult to replace the batteries of the sensors. Wireless power transfer is promising to eliminate the need for battery replacement by recharging the batteries through electromagnetic waves. However, long-distance wireless charging is needed in most agricultural applications. Wireless power transfer under extreme environments, such as underground and underwater, is also a challenge that needs to be studied in the future. Photovoltaic agricultural IoT [43] is presented recently, in which agricultural activities and electricity production coexist in the same area. In this case, distributed wireless chargers are capable of supplying energy to sensing devices, but adaptive task scheduling of energy transfer is an issue due to the diversity of sensing devices for agricultural applications. Furthermore, ambient energy harvesting is another solution toward sustainable agricultural IoT. Some pilot studies have shown that sensor nodes could harvest energy from rivers [44], fluid flow, movement of vehicles [45], and ground surface [46]. But the power conversion efficiency needs to be further improved since the converted electrical energy is limited at present.

c) Cross-media and cross-technology communication: The diverse nature of agricultural environments means that a single standard network solution is not sufficient for all the applications. Likewise, agricultural sensing devices are distributed at indoor greenhouses, outdoor farmlands, underground areas, or, even, water areas. The diversity of the environment means that different types of wireless communication methods based on radio frequency, sonar, vibration, and other signals are needed for information exchange. Hence, it is necessary to examine the performance of different wireless communication methods in each situation to determine the suitable technologies. Cross-media communication between underground, underwater, and air [47] is also crucial toward the complete incorporation of smart sensing into agricultural environments. Similarly, requirements in terms of network size, node density, transmission distance, throughput, and latency are diverse for different agricultural purposes. The diverse applications of IoT in agricultural environments mean that cellular-based networks, 802.15.4 mesh networks, Bluetooth-low-energy networks, and LoRa networks would coexist in the same location. Therefore, cross-technology communication under different physical layers [48] is a fundamental research issue to improve the interoperability in agricultural IoT.

d) Robust wireless networks: The complex agricultural environment poses severe challenges to reliable wireless

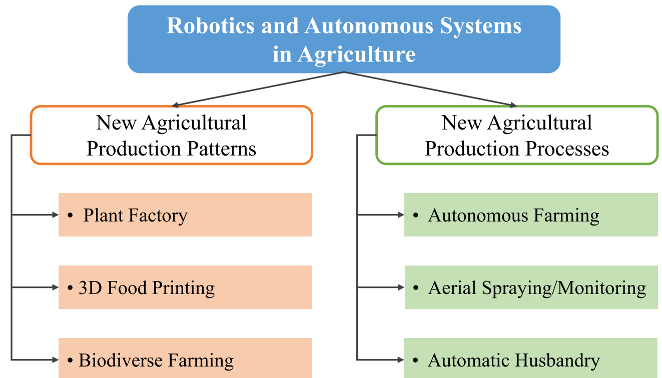

Fig. 3. Six key applications of RAS in the agricultural industry.

communication. First, experimental results have shown that temperature variations significantly affect the reliability of 802.15.4 mesh networks [49] and LoRa networks [50] in both packet reception and received signal strength. It was also demonstrated that radio signal strength is associated with relative humidity [51]. Second, human presence, movement of animal, plant, and other obstacles lead to the fluctuations in the received signal strength due to multipath effect. Therefore, robust network protocols are needed to cope with the changing weather conditions and the dynamic agricultural environment. Third, heterogeneous agricultural IoT networks and dense deployment would cause severe wireless interference and degrade the quality of service. To mitigate this issue, efficient channel scheduling between heterogeneous sensing devices, cognitive radio-assisted WSNs, and emerging networking primitives, such as concurrent transmission [52], are expected to be further explored for agricultural applications.

B. Robotics and Autonomous Systems (RAS)

1) Key Applications of RAS in Agriculture: RAS, an integration of many emerging technologies (such as robotics, computer vision, AI, and control systems), have been widely used in industrial manufacturing to increase productivity, improve the reliability of products, and replace human to do repetitive tasks. Meanwhile, agricultural production is being fundamentally transformed by applying RAS into the agricultural industry.

As shown in Fig. 3, plant factory, 3-D food printing, and biodiverse farming are three key applications that have the potential to be new agricultural production patterns in industrial agriculture. At present, it is difficult to expand the world's agricultural land to preserve forestation. More than 20% of farmland in the world is heavily degraded, and the rest of the agricultural area is under threat. Plant factory [53] looks promising to meet global food demand and sustainable use of natural resources. 3-D food printing [54] is becoming an alternative to produce food in an automated additive manufacturing manner. In biodiverse farms, multiple crops are grown simultaneously on a farmland. The crop diversity helps to make soil nutrients more balance, and to protect against diseases and pests. With the help of agricultural robotics, limitations, such as low productivity and intensive manual labor, could be solved. It should be noted

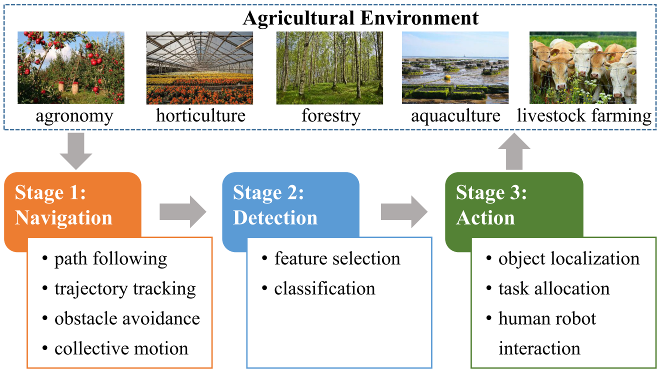

Fig. 4. Core operation stages in agricultural robotics along with key tasks [66].

that biodiverse farming also increases the complexity in the application of agricultural robotics due to variation in detection, classification, harvesting, and other agricultural activities. The technical challenges will be discussed later on.

On the other hand, RAS is also transforming the agricultural production process, where the key applications include autonomous farming, aerial spraying and monitoring, automatic animal husbandry, etc. Smart tractors [55] would work collaboratively to generate operational routes and intelligently avoid barriers in the field to ensure the safety for both farmland and humans. Robotic weeders [56] can differentiate weeds from crops through computer vision, and then precisely spray the herbicide on weeds only or directly eradicate them without harming the crops. Picking and harvesting robots [57] help farmers to collect tomatoes, citrus, apples, and strawberries more efficiently. They recognize fruits and vegetables in the field, determine their location, and harvest the ripe ones in boxes. Since operating speed is dozens of times faster than ground machines, aerial crop spraying and monitoring [58] has attracted considerable attention recently. Finally, RAS also contribute to animal husbandry, such as automatic feeding, milking, and herding.

2) Research Challenges of RAS in Agriculture: We can see that, from Fig. 4, three research challenges in agricultural RAS are autonomous navigation, accurate detection, and intelligent action. The detail discussions are presented as follows.

a) Autonomous navigation: In the first stage, RAS should make sense of the target in the agricultural environment to fulfill path following [59], trajectory tracking [60], obstacle avoidance [61], or collective motion [62]. Accurate guidance is extremely important since it affects crop protection, human safety, operation costs, and work efficiency. Currently, the global navigation satellite system, camera vision, and laser imaging detection and ranging (LIDAR) scanner are three popular techniques for autonomous driving. However, each one has limitations when used alone in agricultural environments. For example, satellite signal attenuation and multipath effects frequently occur in orchards and greenhouses [63]. The performance of computer vision-based navigation system is often degraded due to unstable light conditions in farm fields and plant growth [64]. Although LIDAR scanner based navigation systems outperform the other two approaches in orchard and grove scenarios, the overhanging tree branches, moving objects, and other obstacles affect its performance on tree row detection [65]. Therefore, novel guidance algorithms and control strategies are needed. Moreover, the combination of these techniques with data fusion is helpful to ensure navigation accuracy and robustness.

b) Accurate detection: In the second stage, the two urgent tasks are suitable biological feature selection and robust object classification for the following reasons. First, multispectral image is commonly chosen as a feature in selective spraying and mechanical weeding removal applications, so that the agricultural robots can differentiate weeds from crops. However, the dynamic and complex farm environment makes it challenging to precisely classify plants because of the changing appearance, growth stage, weather condition, object overlapping, or even partial occlusion [67], [68]. Second, the robots used for automatic harvesting should be capable of identifying the different types of fruits and vegetables, their maturity, size, texture properties for precision picking, quality grading, and other purposes. Unfortunately, the different kinds of plants and unstructured orchard with dynamic environmental conditions lead to performance degradation [69] when classical pattern recognition methods are applied to agricultural practices. Unreliable classification methods would undoubtedly cause serious losses to agricultural production. Third, the large fields in breeding nurseries need to be rapidly monitored in a short duration for the germinated crop detection so that the best plant seeds can be found for future breeding. This requires fast classification methods to distinguish the good and bad crop seeds germination [70]. Therefore, there is a need to solve these problems for the improvement in detection accuracy and operational effectiveness.

c) Intelligent action: Finally, the specific tasks, such as robot-assisted plant phenotyping [71], fruit counting and harvesting [72], leaf peeling [73], selective spraying [74], and 3-D mapping [58], are completed during action stage. Three fundamental research concerns are object localization, task allocation, and human–robot interaction. Accurate object localization is the core requirement to ensure inerrant operations and minimize the external influences from the surroundings. Optimized task sequence planning of individual agricultural robot systems and coordination between multiple robots are critical to improving performance in terms of energy efficiency, time consumption, and reliability. Human–robot interaction has been widely studied in the industrial domain, but the progress in agriculture is still nascent. Proper interaction between farmers and autonomous agricultural machinery are extremely necessary to improve productivity, profitability, and prevent potential accidents [75]. Last but not least, robotic arm design is equally important as different types of grippers need to be developed for enhancing the effectiveness and efficiency following their specific applications.

C. Artificial Intelligence (AI)

1) Key Applications of AI in Agriculture: As demonstrated above, AI plays an important role in RAS. With classification, logistic regression, association analysis, and decision-making capabilities, AI is also being applied to other applications in

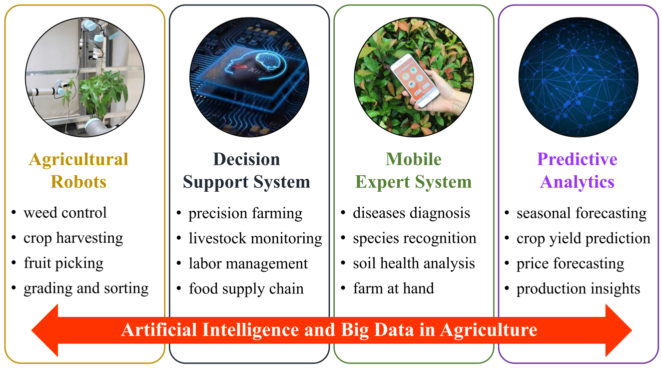

Fig. 5. Key applications of AI and big data in agricultural industry.

agriculture, such as an agricultural decision support system (ADSS), a mobile agricultural expert system, and agricultural predictive analytics.

Four use cases of an ADSS are reviewed in [22], which includes mission planning, water resources management, climate change adaptation, and food waste control. While a recent work [24] focused on the review of crop data management, in which its decision-making capability enabled by ADSS was presented. Moreover, intelligent animal health monitoring systems are a major focus of today's research and drive the growth of AI in agriculture markets. Animal wearables, computer vision systems, and other sensing devices can capture the status of animals in real time. Then, the intelligence engine helps analyze livestock health, animal welfare, production, etc. In recent years, many technological advances have been made in the area of intelligent animal health monitoring. The advancement in biosensors was summarized in [76] and [77]. Machine vision approaches for animal behavior detection were reviewed in [78]. A recent study [79] systematically discussed the ADSS for intelligent aquaponics. Also, a pilot study [80] shows that digital twin technology is helpful to prevent animal diseases in livestock.

As shown in Fig. 5, a mobile expert system is another key application of AI in agriculture. Farmers can now easily use smartphones to identify plant pests and diseases [81]. They are also able to identify soil problems on their own with the help of mobile apps. In addition, the progress of farmland can be tracked by satellite imagery, which is then analyzed by an AI engine. Mobile apps simultaneously visualize the result so that farmers could understand the status remotely. Finally, AI-enabled agricultural predictive analytics and big data technology are capable of forecasting weather conditions, predicting crop yields, modeling agricultural market volatility, and performing price estimation. Based on these observations, professional insights in production can be provided to farmers, as well as to guide companies to optimize business resources.

2) Research Challenges of AI in Agriculture: Although these applications are promising, agriculture is one of the most challenging practical areas for AI for the following reasons.

a) Hard to find single standard solution: Unlike the standardized industrial environment, the conditions in the agricultural field are constantly changing, making statistical quantification difficult. All the factors, such as weather, soil quality, and visited pests, have an impact on AI's performance. As a result, a machine learning (ML) algorithm that performs a task well in one field may fail in neighboring fields, not to mention in other regions.

b) Gap between farmers and AI researchers: Seamless translation from agricultural problems to decision-making models is crucial for the success of adopting AI in agriculture. Farmers are often met with a lot of difficulties in the agricultural production process, but AI researchers are not aware of these agricultural problems, which could be fixed by AI technology. More importantly, AI is practical only after the nature of these agricultural problems and solutions are fully understood. However, AI researchers usually do not know much about professional agricultural knowledge. Thus, it is important to link farmers, agricultural professionals, and AI researchers together to bridge the gap.

c) Distributed secure ML: To successfully implement an artificial neural network, an fuzzy control system, and other AI engines in agriculture, a huge amount of data are needed to train AI models. However, the related data on agriculture are much less than that in the industrial field due to the lack of digitization in agriculture, inaccessible data, as well as privacy protection issues. With the help of deploying 5G infrastructure in rural areas [82], SAGUIN, and novel sensors, massive agricultural data could be collected in the future. Novel ML techniques, such as federated learning [83], are expected to be explored for farm data protection in agricultural AI applications.

D. Big Data Analytics

1) Key Applications of Big Data in Agriculture: IoT helps collect data in every step of the agricultural production and agri-food supply chain management. Thus, it would also be beneficial to implement big data analytics during food production, processing, logistics, and marketing. Data-driven agricultural industry would profoundly transform the production and consumption behaviors [12]. For instance, ADSS, mobile agricultural expert system, and agricultural predictive analytics all rely on the power of big data, which can provide smart recommendation to farmers toward precision farming [84]. Accurate risk assessment could help farmers to better manage agricultural risks in terms of production, market, institutional risk, along with personal and financial risk [85].

Moreover, big data plays a key role in agri-food supply chain management in addressing to solve food safety, imbalance supply, as well as food loss and waste. For example, the data-driven agricultural solution for sustainability management in the by-products supply chain was introduced in [15]. A comprehensive discussion about the impacts of big data analytics on the agri-food supply chain was presented in [25], from multiple perspectives, including functional impact, economic impact, environmental impact, social impact, business impact, and technological impact.

2) Research Challenges of Big Data in Agriculture: Recent literatures [25], [84], [86] have presented comprehensive discussions on the challenges of adopting big data analytics in agriculture. Our observations are summarized as follows.

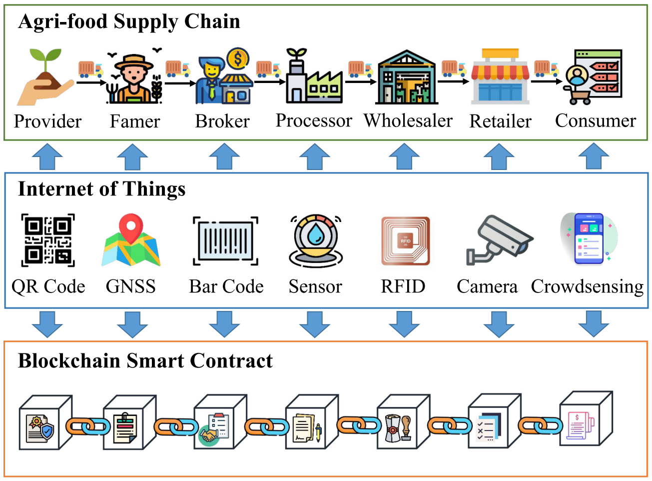

Fig. 6. Blockchain smart contract for traceable agri-food supply chain.

a) Technical issues: The IoT can provide fine-grained monitoring for every aspect during food growing, processing, transportation, and retailing, which means that the problem of agricultural data scarcity would be solved. However, it is challenging to integrate disparate data as that come from thousands of individual farmlands, animal factories, and enterprise applications. Therefore, data interoperability is essential to maximize the value of massively dispersed data after systematic data collection, storage, processing, and knowledge mining. On the other hand, the lack of decentralized ML and data management systems decreases the willingness of multiple actors to share agriculture data. Plant phenotyping is particularly important for agricultural and ecological sciences to investigate the interaction between genotype, environment, and phenotype. Thus, an agricultural information system is expected to track environmental parameters and metadata associated with plant growth [87]. In this regard, the ability to link objects and corresponding events, as well as tracking the occurrences of every event in the spatial–temporal scale, and mining biological knowledge should be greatly improved. Last but not least, attention still needs to be paid to other technical issues regarding decision support tools, data quality, security, storage, and openness.

b) Social issues: Farmer participation is a key factor toward the success of big data in agriculture. It is therefore necessary to demonstrate practical benefits for farmers, so that they are willing to participate in the value chain of agricultural data exchange. Another hurdle is the shortage of agricultural big data experts. Most skilled big data engineers, data analysts, and scientists are not at agricultural universities or agriculture-related enterprises. The cultivation of interdisciplinary talents with rich knowledge of agriculture and big data analytics would be one possible solution to bridge the gap.

E. Blockchain

1) Key Applications of Blockchain in Agriculture: Smart contract (or distributed ledger technology) and cybersecurity are two key applications of blockchain in agriculture. Fig. 6 demonstrates a blockchain-based smart contract for traceable agri-food supply chain. The IoT provides fine-grained sensing throughout the entire supply chain. With smart contract, all the transactions are recorded in a decentralized manner. An immutable transaction history from providers of raw materials to consumers would help to improve food quality control, increase traceability, and, finally, overcome food safety issue. The digital transformation of the agri-food supply chain is expected to be enabled by blockchain-based smart contract technologies toward a traceable, transparent, trustful, and intelligent ecosystem.

Many blockchain-based smart contract solutions have been proposed in recent years. For example, a practical implementation of a blockchain-based traceability solution, called AgriBlockIoT [88], was presented at the IoT Vertical and Topical Summit on Agriculture. A blockchain-based smart contract approach for soybean traceability was proposed in [89]. The application of the grain supply chain with blockchain was demonstrated in [90]. Other related studies were shown in [91] and [92]. Similarly, smart contract for agriculture is paid great attention by many blockchain startups, such as AgriLedger, AgriDigital, AgriChain, and Ripe. All of them have proposed their solutions for the agri-food supply chain management.

Cybersecurity is important in every facet of society, including our daily life, business management, industrial production, and, not to mention, the agricultural sector. Data integrity attacks through data tampering and rogue data injection are the first threat in precision farming applications. For example, a smart irrigation system would schedule the wrong watering run times because rogue data are inputted into an AI module running the system. The second threat is confidentiality attacks through packet sniffing and system backdoor. Farmers would suffer a great deal of financial loss and negative emotional impacts if sensitive agricultural information, such as crop yields, cultivation methods, and livestock health conditions, are disclosed to third parties. The third threat is agricultural IoT network attacks against availability through the distributed denial of sleep [93], malicious reporting, and other attacks. For instance, the embedded sensing devices would quickly exhaust energy under the denial of sleep attacks. The false instructions and information reporting from malicious nodes would lead to serious consequences and even disasters in autonomous farming and smart livestock production.

These observations demonstrate that wireless network defense and privacy protection are crucial in the agriculture domain. The security and privacy solutions for IoT applications are surveyed in [23]. Interestingly, it discussed the adaption of these approaches into agriculture and analyzed blockchain-based privacy protection for agriculture applications.

2) Research Challenges of Blockchain in Agriculture: The adoption of blockchain during agri-food production and supply chain management is an opportunity to improve traceability, transparency, and trust among providers, farmers, suppliers, retailers, and consumers. However, many technical bottlenecks need to be resolved to adopt blockchain technology in agriculture. These bottlenecks are listed as follows.

a) Interoperability: Currently, thousands of blockchain projects are active. They are developed on a wide variety of platforms with different programming languages, protocol stacks,

TABLE III
TAKE-HOME MESSAGES OF ENABLING TECHNOLOGIES TOWARD AGRICULTURE 4.0

Enabling Technology	**Key Application**	**Research Challenge**
Internet of Things	• Space-Air-Ground-Undersurface Integrated Network • Precision Farming • Livestock and Fishery Monitoring • Smart Greenhouse	• Professional Agricultural Sensors • Wireless Power Transfer & Ambient Energy Harvesting • Cross-Media & Cross-Technology Communication • Robust Wireless Networks
Robotics	• Plant Factory • 3D Food Printing • Biodiverse Farming • Autonomous Farming • Aerial Spraying & Monitoring • Automatic Husbandry	• Autonomous Navigation • Accurate Detection • Intelligent Action
Artificial Intelligence & Big Data Analytics	• Agricultural Robot • Agricultural Decision Support System • Mobile Agricultural Expert System • Agricultural Predictive Analytics	• Hard to Find Single Standard Solution • Gap between Farmers and AI Researchers • Distributed Secure Machine Learning • Technical and Social Issues with Big Data
Blockchain	• Smart Contract • Cybersecurity	• Interoperability • Scalability • Energy Consumption • Security and Privacy

and security mechanisms. The lack of interoperability leads to network isolation problems, where the different types of blockchain networks can hardly communicate with each other. To integrate existing blockchain networks, it is necessary to propose novel architecture, interoperable communication protocol, and improved middleware so that efficient cross-blockchain communication [94], [95] is realized.

b) Scalability: Unlike the Visa transaction network, which is capable of processing thousands of transactions in a second, the transaction speed in blockchain-based smart contract networks, such as Bitcoin and Ethereum, are less than 20 per second [96]. Fast response time and high network throughput are essential since innumerable transactions need to be processed when millions of actors in the entire supply chain are involved in the integrated networks.

c) Energy consumption: Apart from the huge amount of energy expended by bitcoin mining, the complex consensus mechanisms in transaction validation also lead to high energy consumption. Therefore, it is necessary to reduce the complexity of blockchain networks for cost savings. For example, the concept of proof-of-stake (PoS) [97] has been proposed for lightweight distributed consensus.

d) Security and privacy: The immutable data storage, decentralized network, and peer-to-peer communication are three key features of blockchain technology that make it promising to enhance security and privacy for IoT. For example, Salman *et al.* [98] presented a systematic review of blockchain-based security services solutions, including authentication, confidentiality, privacy, and integrity assurance. However, like other popular network technologies, blockchain has become a target for hackers, who can launch cyber-attack from the protocol side, implementation side, and logical defect. A detailed survey on cyber-attack in a blockchain network and recent advances can be found in [99].

IV. CONCLUSION

Monoculture and intensive animal farming are the main agricultural production patterns in today's industrial agriculture. However, the damage to the ecological environment, public health, and animal welfare are big limitations. Although presently, the agricultural production process is mechanized and informatized, the lack of digitization and intelligence are major obstacles to improving the automation capability. Moreover, the agri-food supply chain at the current stage is not intelligently managed. To address these issues, it is essential to integrate emerging Industry 4.0 technologies into agriculture. Hence, in this article, we presented detailed discussions on the key applications and research challenges when these technologies met agriculture. For the ease of readers, the take-home messages are summarized in Tables II and III.

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Ye Liu (Member, IEEE) received the M.S. and Ph.D. degrees in electronic science and engineering from Southeast University, Nanjing, Nanjing, China, in 2013 and 2018, respectively.

He was a Visiting Scholar with Montana State University, Bozeman, MT, USA from October 2014 to October 2015. He was a visiting Ph.D. Student from February 2017 to January 2018 with the Networked Embedded Systems Group, RISE Swedish Institute of Computer Science. He is currently a Researcher with Nanjing Agricultural University, Nanjing, China. He has authored or co-authored papers in several prestigious journals, such as the *IEEE Communications Magazine*, IEEE INTERNET OF THINGS JOURNAL, *ACM Transactions on Embedded Computing System*, and IEEE NETWORK. His current research interests include wireless sensor networks, energy harvesting systems, and mobile crowdsensing.

Dr. Liu was awarded the 1st place of the EWSN Dependability Competition in 2019.

Xiaoyuan Ma (Student Member, IEEE) received the B.S. degree in electronic science and technology and the M.S. degree in communication engineering from Shanghai Jiao Tong University, Shanghai, China, in 2010 and 2014, respectively. He is currently working toward the Ph.D. degree in signal and information processing with the Shanghai Advanced Research Institute, Chinese Academy of Sciences (CAS), Shanghai, China.

He joined the Safety and Emergency Laboratory, Shanghai Advanced Research Institute, CAS, Beijing, China, in 2011. His current research interests include low-power embedded wireless systems (BLE, Zigbee, or LoRa), dependable IoT communication, implementations of embedded system, and IoT network test tools. The network protocols proposed by him are able to work dependably under interference, which are awarded by EWSN'17-19 Dependability Competitions with respect to reliability, latency, and energy consumption.

Lei Shu (Senior Member, IEEE) received the B.S. degree in computer science from South Central University for Nationalities, Wuhan, China, in 2002, the M.S. degree in computer engineering from Kyung Hee University, Seoul, South Korea, in 2005, and the Ph.D. degree in computer engineering from the Digital Enterprise Research Institute, National University of Ireland, Galway, Ireland, in 2010.

Until 2012, he was a Specially Assigned Researcher with the Department of Multimedia Engineering, Graduate School of Information Science and Technology, Osaka University, Osaka, Japan. He is currently a Distinguished Professor with Nanjing Agricultural University, Nanjing, China, and a Lincoln Professor with the University of Lincoln, Lincoln, U.K. He is also the Director of the NAU-Lincoln Joint Research Center of Intelligent Engineering, Nanjing, China.

Dr. Shu was on multiple Editorial Boards, including the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, *IEEE Communications Magazine*, *IEEE Network Magazine*, IEEE SYSTEMS JOURNAL, IEEE ACCESS, and IEEE/CCA JAS.

Gerhard Petrus Hancke (Senior Member, IEEE) received the B.Eng. and M.Eng. degrees in computer engineering from the University of Pretoria, Pretoria, South Africa, in 2002 and 2003, respectively, and the Ph.D. degree in computer science from the Security Group, Computer Laboratory, University of Cambridge, Cambridge, U.K., in 2009.

He is currently an Associate Professor with the Department of Computer Science, City University of Hong Kong, Hong Kong, China. His current research interests include system security, embedded platforms, and distributed sensing applications.

Dr. Hancke is an Associate Editor for the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE OPEN JOURNAL OF THE INDUSTRIAL ELECTRONICS SOCIETY, *IET Smart Cities*, and Area Editor of *Ad Hoc Networks*.

Adnan M. Abu-Mahfouz (Senior Member, IEEE) received the M.Eng. and Ph.D. degrees in computer engineering from the University of Pretoria, Pretoria, South Africa.

He is currently a Principal Researcher with the Council for Scientific and Industrial Research (CSIR), a Professor Extraordinaire with Tshwane University of Technology, Pretoria, South Africa, a Visiting Professor with the University of Johannesburg, Johannesburg, South Africa, and an Extraordinary faculty member with the University of Pretoria, Pretoria, South Africa. He is the founder of the Smart Networks collaboration initiative that aims to develop efficient and secure networks for the future smart systems, such as smart cities, smart grids, and smart water grids. His current research interests include wireless sensors and actuator networks, low-power wide area networks, software defined wireless sensor networks, cognitive radio, network security, network management, and sensor/actuator node development.

Dr. Abu-Mahfouz is an Associate Editor for the IEEE ACCESS, IEEE INTERNET OF THINGS, and IEEE TRANSACTION ON INDUSTRIAL INFORMATICS, and Member of many IEEE Technical Communities.