Edge Computing for Internet of Everything: A Survey

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***Abstract*—In this era of the Internet of Everything (IoE), edge computing has emerged as the critical enabling technology to solve a series of issues caused by an increasing amount of interconnected devices and large-scale data transmission. However, the deficiencies of edge computing paradigm are gradually being magnified in the context of IoE, especially in terms of service migration, security and privacy preservation, and deployment issues of edge node. These issues can not be well addressed by conventional approaches. Thanks to the rapid development of upcoming technologies, such as artificial intelligence (AI), blockchain, and microservices, novel and more effective solutions have emerged and been applied to solve existing challenges. In addition, edge computing can be deeply integrated with technologies in other domains (e.g., AI, blockchain, 6G, and digital twin) through interdisciplinary intersection and practice, releasing the potential for mutual benefit. These promising integrations need to be further explored and researched. In addition, edge computing provides strong support in applications scenarios, such as remote working, new physical retail industries, and digital advertising, which has greatly changed the way we live, work, and study. In this article, we present an up-to-date survey of the edge computing research. In addition to introducing the definition, model, and characteristics of edge computing, we discuss a set of key issues in edge computing and novel solutions supported by emerging technologies in IoE era. Furthermore, we explore the potential and promising trends from the perspective of technology integration. Finally, new application scenarios and the final form of edge computing are discussed.**

***Index Terms*—6G, artificial intelligence (AI), blockchain, digital twin (DT), edge computing, microservices.**

I. Introduction

BENEFITTING from the rapid development of underlying technologies, the Internet of Things (IoT) has increasingly permeated our lives and become an essential part of our daily activities. Millions of devices/sensors are continuously generating data and exchanging important messages through complex network infrastructures that enable machine-to-machine communication [1], [2]. Statista [3] estimated that installed bases of IoT devices worldwide will reach 30.9 billion units by 2025, a significant increase from the 13.8 billion units expected in 2021. This indicates that sensors, actuators, and other intelligent devices will generate massive data at a fast speed, and these massive data need to be further processed. However, the core network bandwidth is becoming the bottleneck when moving all computing tasks to the cloud servers in cloud computing. Moreover, cloud computing is hard to meet the demands of low cost, high performance, and ultralow latency of some time-sensitive applications (e.g., interactive cloud applications and cooperative autonomous driving) due to its property of centralization. In this context, edge computing is proposed as a promising means to solve the shortcomings in cloud computing. Edge computing adopts an open platform with core network capabilities, computing resources, and data storage to provide users with nearest-end services, which is regarded as the critical enabling technology toward the 5G era. Edge computing is not a substitute for cloud computing but a supplement and expansion, which is ideal for real-time data analysis and intelligent processing.

In recent years, this world has witnessed the dawning of the Internet of Everything (IoE) era. People, process, data, and things are intelligently connected to the Internet and continuously create the value. However, IoE is magnifying the inherent limitations of the existing computing models, especially edge computing. Some issues of edge computing architecture, including service migration, security and privacy preservation, and deployment issues of edge node, are difficult to be efficiently addressed by using conventional methods. Thanks to the rapid development of upcoming technologies, novel solutions have emerged and have the potential to alleviate these challenges. As for service migration, the reinforcement learning (RL) solves the service migration issue by using the Q-learning algorithm to maximize the return of migration and reduce the communication cost and migration cost of user equipment [4], [5]. In terms of security and privacy preservation, the federated learning enables users to collaboratively train an algorithm and keep local data samples on the device, effectively avoiding privacy by uploading only parameters such as weights [6], [7]. The blockchain technology [8], [9], [10] maintains users' changeable keys and ensures security and privacy of the edge network without metadata disclosure by nodes during edge coordination. Regarding node deployment issues, microservices can integrate the various

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aspects of IoT system architecture layers to facilitate distributed software development, which addresses the challenge concerning the deployment issue of application package [11].

Edge computing research lies at the intersection of the computing model and other disciplines, where the existence of many research opportunities has resulted in a highly active area. In addition to solving the challenges mentioned above, the convergence of edge computing and some technologies (some of them mentioned above), including artificial intelligence (AI), blockchain, 6G, and digital twin (DT) driven by other technologies, can fully unleash their potential and benefit from each other. The mutual benefit of integration between different disciplines deserves further exploration and research. Moreover, new application scenarios have also emerged, especially in the COVID-19 pandemic era, gradually changing our daily lives, including remote-working, the new physical retail industry, and digital advertising. Although a number of efforts have been conducted, the discussion about novel solutions to existing challenges of edge computing and future directions supported by emerging technologies is missing in other surveys.

In this work, we summarize existing efforts and previous work and present our view on future directions of this research field. We try to provide a state-of-the-art survey of edge computing, focusing on existing challenges and a series of opportunities from the perspective of integration with emerging technologies in the IoE era. The main contributions of this article are outlined as follows.

1) We summary several key challenges in edge computing including service migration, security and privacy preservation, and deployment issues of edge node. Meanwhile, the novel solutions supported by emerging technologies (e.g., deep learning (DL), blockchain, and microservices) are discussed.
2) We further point out the promising prospects from the technology integration perspective, including AI, blockchain, 6G and DT, and explore their potential and mutual benefit.
3) The new application scenarios supported by edge computing, especially in the COVID-19 pandemic, including remote-working, new physical retail industry, and digital advertising are discussed. We further propose the edgeless computing, which is the ultimate form of edge computing.

Related Surveys: One of the most important literature surveys of this field is the work by Shi *et al.* [12]. Their work gave a formal definition of edge computing in academia and pointed out the challenges. However, their proposed solutions to the existing challenges of edge computing are traditional. They did not examine the opportunities brought by emerging technologies. Khan *et al.* [13] highlighted the core applications and importance of edge computing in real-life scenarios. Nevertheless, their work did not adequately discuss the possibilities provided by upcoming technologies and future trends of edge computing. Varghese *et al.* [14] discussed the opportunities and challenges in this area, but the two parts are discussed separately and are not fully connected. Carvalho *et al.* [15] provided another up-to-date survey of the field. Their work focused on use cases for each edge computing architecture and future research directions. A discussion of combining edge computing with technologies from other disciplines is missing therein. We particularly conduct in-depth discussions on novel solutions to existing challenges in this field as well as promising trends from the perspective of convergencing edge computing paradigm with other emerging technologies in IoE era.

The remainder of this article is organized as follows. In Section II, we briefly present the overview of edge computing, including definition, five important concepts, and characteristics. Section III describes several significant challenges of edge computing and corresponding solutions supported by integrating with upcoming technologies. Our work is focused on Section IV, where we explore the mutual benefits of the integration of emerging technologies and edge computing, discuss some new application scenarios and finally, propose the final development form of edge computing paradigm. Finally, we conclude our work in Section V.

II. Overview of Edge Computing

In this section, a brief overview of several edge computing concepts, including mobile cloud computing (MCC), mobile edge computing (MEC), fog computing, cloudlet computing, and the most popular collaborative cloud–edge–end framework in recent years, is presented.

A. *Paradigms of Edge Computing*

In a conventional cloud-centric model, data collected by various terminal devices, such as photos, videos, and the surrounding environment must be transferred to the cloud center for processing and then, the results are sent back [16]. The increasing amount of terminal devices and large-scale data transmission has posed a significant challenge to cloud computing, especially efficiency, energy usage, and latency issues. The emergence of edge computing has the potential to deal with these challenges. Satyanarayanan [17] defined edge computing as a new computing model that deploys computing and storage resources (such as cloudlets, microdata centers, and fog nodes) at the edge of the network closer to mobile devices or sensors. The "edge" is regarded as any computing resource and network between cloud and terminal devices [12]. Generally speaking, the structure of edge computing is generally divided into three layers: 1) terminal layer; 2) edge layer; and 3) cloud layer. This hierarchy depicts the computational capabilities of edge computing elements and their properties, as shown in Fig. 1.

Despite the rapid development of edge computing, the edge computing community has yet to come to an agreement on its standardized definitions, architectures, and protocols [18]. There have been various architectures at the edge, including MCC, MEC, fog computing, and cloudlet computing. Although their concepts overlap and the boundaries are not particularly obvious, we still have appropriate characteristics to distinguish them. Tables I and II depict the main comparisons amongst them, including attribute and feature. It is worth noting that when MCC employs cloudlet as part of its design, the

TABLE I
ATTRIBUTES AMONGST FOUR COMMON EDGE COMPUTING MODELS

Attribute	Mobile Cloud Computing	Mobile Edge Computing	Fog Computing	Cloudlet Computing
Key Features	Rich mobile applications to be executed on a different number of mobile devices.	Extend the concept of edge computing to Wi-Fi and other non-3GPP access scenarios.	The network service is not only a data pipeline but also a pipeline of data processing.	1. Data center in a box. 2. Dynamic VM synthesis.
Context Awareness	High	High	Medium	Low
Mobility Management	Not specified	Yes	Not specified	Not specified
Computing Power	Low on mobile devices	High	Not specified	Not specified
Application Portability	High	High	Not specified	Not specified
Latency	High	Low	Not specified	Not specified
Location for Computing	Special dedicated buildings	Base stations and nearby devices	Devices along the routing path	Nearby cloudlets
Access Mechanisms	Bluetooth, Mobile Networks	Mobile Networks	Bluetooth, Wi-Fi, LAN	Wi-Fi, LAN, WAN
Energy Consumption	Low	Low	Low	Low on mobile devices
Availability	High	Average	High	Moderate
Service Type	Local	Less global	Less global	Local
Standardzation Organizations	NIST	ETSI, 3GPP	OpenFog Consortium, IEEE	OpenEdge
Power Consumption	Low on mobile devices	High	Low	Moderate
Primary Motivator	Academia	Academia/Industry	Academia/Industry	Academia
Distance from Users	Far	Close	Relatively close	Close
Architecture	Central cloud with distributed mobile devices	Localized/hierarchial	Decentralized/hierarchical	Localized
Security	Need to be offered on mobile terminals and along cloud-to-things	Need to be offered on edge network equipment (RAN, AP)	Need to be offered on participant nodes	Need to be offered on participant nodes
Virtualization at the Edge	Yes	Yes	Not specified	Yes, extends OpenStack

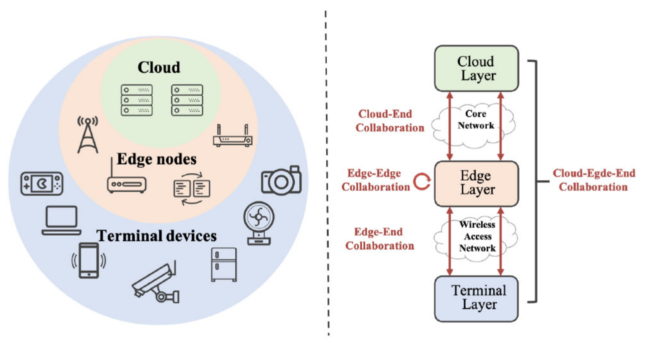

Fig. 1. Three layers of edge computing architecture and collaborative cloud–edge–end framework.

qualities are identical to those listed in the corresponding column. Moreover, cloud–edge–end collaboration has emerged as the most popular operational framework for edge computing in recent years. In our work, this group of emerging technologies is uniformly referred to as "edge computing." In this section, several conceptions of edge computing are introduced.

1) Mobile Cloud Computing: The increasing usage of mobile devices has occupied our lives and affected our way of life [19], [20]. Entertainment, games, social networks, and other applications-based mobile terminals are becoming more and more abundant. However, there are many restrictions, such as computing, storage capacity, and shared wireless medium. Cloud computing is a way to host the execution of applications by moving mobile devices to an integrated environment other than itself, which can solve those issues in mobile computing. According to [21], MCC, at its simplest, refers to an infrastructure where both data storage and data processing happen outside of the mobile device. Mobile cloud applications offload computational power and data storage from mobile phones to the cloud, enabling smartphones and other mobile users to access applications and mobile computing. MCC is becoming the dominant way to run mobile applications [22].

2) Mobile Edge Computing: MEC is regarded as a critical technology and architectural concept for the transition to 5G [23], [24]. The European Telecommunications Standards Institute (ETSI) [25] defined it as an IT service environment by providing cloud computing capabilities at the edge of a mobile network, aiming to extend the concept of edge computing to Wi-Fi and other non-3GPP access scenarios. MEC is logically independent of other network parts and is suitable for supporting high-security applications. Additionally, MEC servers often have a strong computational capacity, making them ideal for analyzing and processing large amounts of data. MEC also supports the perception of edge applications, especially the wireless access part. The MEC node can obtain real-time network data, such as base station ID, available network bandwidth, and information related to the user's location, thereby achieving link-sensing adaptation [26]. Moreover, MEC technology enables mobile network operators to offer additional network information and congestion management capabilities to third-party developers, increasing the number of applications and services available to consumers.

3) Fog Computing: In 2012, Cisco proposed the concept of fog computing, which comes from the fact that "fog" is closer to the ground than clouds. Fog computing can be treated as the combination of MCC and MEC.

TABLE II
FEATURES AMONGST FOUR COMMON EDGE COMPUTING MODELS

Feature	Mobile Cloud Computing	Mobile Edge Computing	Fog Computing	Cloudlet Computing
Requirements for Infrastructure	Yes	Yes	Yes	Yes
Ultra-low Latency	No	Yes	Yes	Yes
Distributed Geographically	No	Yes	Yes	Yes
Support for Multiple IoT Applications	No	No	Yes	Yes
Standardized	Yes	Yes	Yes	No
Support for Large-scale Application	No	Yes	No	Yes
Support for Real-time Application	No	Yes	Yes	Yes
Location Awareness	No	Yes	Yes	Yes
Support for Heterogeneity	Yes	Yes	No	No

Vaquero and Rodero-Merino [27] defined fog computing as a scenario where a large number of heterogeneous (wireless and sometimes autonomous) and decentralized devices communicate and potentially cooperate among them and perform storage and processing tasks without the intervention of third parties. These tasks can be utilized to support basic network functions or new services and applications running in a sandboxed environment. Fog computing establishes a continuum [28] between data centers and data sources to provide users with computing, storage, and network services, transforming the network into a "assembly line" for data processing rather than a "data pipeline." Take the vacuum cleaner as an example. Centralized fog nodes (or IoT gateways) continuously collect information about their surroundings from sensors in the home and activate the vacuum cleaner when garbage is detected. But in the edge computing solution, the sensors will judge whether there is garbage, respectively, and then, send a signal to start the vacuum cleaner.

4) Cloudlet Computing: Cloudlet is a concept proposed by Satyanarayanan *et al.* [29] in 2009. They defined cloudlet as trusted, resource-rich computers that provide storage resources and computing near the mobile users (near or coexisting with a wireless access point). The cloudlet originates from the integration of mobile computing, IoT, and cloud computing, which plays the role of "data center in box" [18]. Cloudlet computing consists of three main features: 1) software-only deployment; 2) proximity deployment; and 3) build based on standard cloud technologies. Moreover, cloudlet has become a new alternative technology to carry computing tasks on mobile devices. The challenge of insufficient computing resources of mobile devices by supporting cyber foraging [30] in mobile computing is effectively solved. By implementing cloudlet discovery, virtual machine (VM) provisioning, and VM handoff, cloudlet computing also supports application mobility.

5) Collaborative Cloud–Edge–End Computing: Cloud–edge–end computing is a collaborative processing model that take full advantage of both edge computing and cloud computing. As shown in Fig. 1, it is a decentralized network with cloud as the center and layered construction, including cloud–edge collaboration, edge–edge collaboration, and edge–end collaboration. Edge computing and cloud computing complement and cooperate with each other. Edge servers process data that requires an immediate response. The cloud server provides significant computing capacity and the ability to integrate diverse types of information. Real-time interaction between edge nodes and the cloud can help alleviate the data heterogeneity issues for the cloud [31]. Furthermore, when the storage capabilities of the edge nodes are insufficient, the cloud may store a portion of the data and transfer it to the client via the network as needed, therefore conserving edge storage resources [32]. Cloud–edge cooperation is critical in a variety of application scenarios, including content distribution networks (CDNs), industrial Internet, energy, smart homes, and smart transportation [33], [34], [35], [36]. Hong *et al.* [37] proposed the Intelligent IoT (IIoT)–edge–cloud computing model based on multihop computation-offloading for resource-intensive applications (e.g., 3-D sensing, AI processing, and big data analytics), with the goal of reducing energy consumption and processing delay. For strengthening 5G heterogeneous network (HetNet) security, Wei *et al.* [38] proposed a federated learning empowered the cloud–edge–end cooperation model. The security is guaranteed by equipping node with an attack detection mechanism at the end, edge, and the cloud of 5G HetNet.

B. Edge Computing Characteristics

Edge computing has some notable features compared to the cloud computing paradigm. Specifically, we discuss three main characteristics that makes up for cloud computing in the context of processing massive data, including low latency computing, more efficient energy consumption, and transferred computing power.

1) Low Latency Computing: The advantage of the centralized architecture of cloud computing is that it is easy to manage and maintain. However, it is no longer the optimal strategy for geographically distributed applications. Some popular location-based social networking applications (e.g., Foursquare, Mingle, and Google Now) require computing power closer to the data source to optimize the system efficiency and user experience [14]. Edge devices generate numerous data streams, and it is impossible to make real-time decisions when analytics is conducted on a remote cloud. For example, Boeing 787 generates 5 GB of data every second [12]. The bandwidth between the aircraft and other satellite equipment or base stations can not withstand such a large amount of data due to long request-to-response links. Consider self-driving cars from Google as another example. A variety of sensors and cameras capture traffic information in real-time, generating nearly 1 GB of data per second for complex data processing and driving decisions. Moreover, Americans drive an average of 600 h a year, equivalent to 2.16 million seconds or about 2 PB of data per vehicle per year [12]. It is almost inconceivable that all data must be sent to the cloud for processing before responding to the results. The response time will be extraordinarily long and become a bottleneck. Certain time-sensitive applications suffer from the same issue and impose strict limits on latency between edge devices and cloud servers. Deploying some of the processing power closer to the user is an effective way to solve the issues in the above scenarios. The adoption of edge computing has the potential to minimize processing latency and network bandwidth requirements.

2) Efficient Energy Consumption: With the rapid development of computing models (e.g., cloud computing), the network bandwidth consumption of novel applications (e.g., video analytics) has increased sharply in recent years. According to the Cisco Visual Networking Index research [39], video streaming services (e.g., YouTube, Hulu, and Netflix) are expected to consume 79 percent of total network bandwidth in 2022. High-bandwidth applications, such as online gaming, ultrahigh-definition (UHD), or 4K video streaming, require a broadband connection with a speed of at least 5 Mbit/s, placing a greater demand on network capacity. The high network bandwidth consumption means high energy exhaustion because a significant amount of electric power to deliver data is required [40]. The emergence of edge computing could help solve this tricky issue by processing more data utilization changes. By building a group of coordination and management system of distributed data centers, edge data centers ensure effective resources utilization. Instead of running 24/7 like a cloud data center, resources will become dormant when they are not needed. Additionally, sensors and IoT devices are being utilized to monitor energy use, assess energy levels in real time, and provide a real-time perspective of consumption, enabling organizations to make dynamic modifications to energy supplement and demand. Meanwhile, cooling data centers requires a certain amount of energy. Due to the decreased size and output of edge data centers, the tiny data center's overall energy consumption will decrease proportionately.

3) Transferred Computing Power: The emergence of intelligent devices, such as virtual reality glasses and face recognition applications altered our way of life profoundly. However, these IoT devices and applications have some constraints in battery life and computing power while executing some complex activities [14]. While moving computing tasks to the remote cloud has proven to be a useful solution, the challenge of execution delays due to data exchange has always been present. Edge computing aims to offload heavy processing from mobile devices to network edge infrastructures such as tiny cell base stations with computing and storage capacity, therefore improving the user experience dramatically. By offering communication capability from the radio access network (RAN) and making computation resources closer to users, it has the potential to significantly reduce latency, prevent network congestion, and extend the battery lifetime of terminal devices.

III. Challenges

Despite the benefits and promising prospect of edge computing, there are still many key issues remaining to be addressed. Especially in IoE era, these major challenges are gradually being amplified. This section discusses several research challenges followed by partial solutions supported by emerging technologies, such as DL technology [41], blockchain technology, and microservices.

A. Service Migration

Application mobility is one of the significant factors that should be taken into account. Although mobility increases the flexibility of applications, it brings new challenges. Computing resources in mobile applications may switch between multiple devices as users move [42]. Resource switching requires migrating the currently running service to another device. The major issues concerning service migration are summarized as follows.

1) How to appropriately select the edge server to migrate the service is a significant issue. The service scope of multiple edge servers may overlap. Hence, if a user moves into a specific area within the service area of multiple servers, it is supposed to think over choosing which server to migrate service. Moreover, the resources available to edge servers are an essential factor to consider. When migrating a current user's service to another edge server, the edge server receiving the service migration should have sufficient resources to satisfy the current user's service requests [43].
2) Migration of services requires consideration of both the duration and cost of the migration. Certain applications are latency-sensitive, which means that low latency must be guaranteed during service migration. Therefore, an appropriate service migration strategy should attempt to minimize total migration time. Moreover, the application providers are mainly concerned with the final revenue. The migration decision requires a tradeoff between migration benefits and migration costs. Designing a migration solution that can optimize migration costs is challenging.
3) The unpredictability of user mobility and the request patterns increase the difficulty of gaining the optimal service migration approach. If the user equipment travels inside a specified region and the borders of the two edge servers are near together due to a particular movement mode, the user equipment's movement will have a dynamic effect on the server performance.
4) The diversity of applications and heterogeneity of edge servers increase the complexity of service migration. Many users and applications must be considered when migrating services. Therefore, migrating ongoing

services is more complicated. If the current migration strategy is used, unreasonable migrations may be repeated.

The mathematical models, such as Markov decision process (MDP) are proposed to make effective service migration decisions. However, the global optimal solution obtained by MDP is based on simple theoretical assumptions, which are subject to the complex condition and a large amount of various parameters. This feature limits the applicability of mathematical models to service migration. Recently, AI technology, especially DL, has provided a promising solution for service migration decisions by considering complex factors, such as heterogeneity of node equipments, the dynamic of network environment, and real-time requirements of users' rapid movement. The DL technology, especially RL can continuously learn from a large amount of historical data, constantly interact with dynamic environments and respond quickly to changes [5], [44]. Especially, RL is able to perceive its environment, take corresponding actions, and identify the optimal action to maximize reward in a given scenario. State, action, and reward are three key elements in whole process. When MEC and RL are integrated, the decision issue of service migration can be alleviated. Hence, three key elements above mentioned have the new representations in the MEC network. The first is "state," which is able to denote the state of the MEC server that user equipments (UE) are currently covered. Next, "action" refers to a list of all available servers to which the current VM can be transferred. The final is "reward," which refers to the mobile user chooses an action mentioned above and gets the final reward. The ultimate goal is to minimize objective function's value and the Q-learning algorithm is utilized to maximize the reward of migration. Hence, there are more rewards for action with lower communication costs and migration costs of user equipment at the MEC network.

B. Security and Privacy Preservation

Compared to the cloud computing paradigm, edge computing can avoid the abuse and theft of users' privacy data on long transmission links by processing partial data at the edge of the network. However, new security and privacy challenges have emerged due to the access of multiclass and multidevice devices in edge networks. The challenges can be denoted as follows.

1) Edge computing devices are usually close to the user. Therefore, MEC nodes adjacent to the user may collect sensitive information [45], [46], including the user's identity, location information, and application usage. Take the smart home system as an example. The hackers can easily track electricity usage to identify whether a house is unoccupied, which increases the possibility of items being stolen in the house. Furthermore, centralized control becomes extremely difficult due to the discrete nature of MEC nodes.
2) Traditional approaches of security and privacy protection, such as certificates and public key infrastructure (PKI) authentication, may not be suitable for being used on edge infrastructures [47]. In dynamic changes of MEC nodes, nodes must mutually verify the newly formed MEC network. In addition, MEC nodes also need to restrict or reject service requests from malicious and compromised nodes.
3) The device communication in the MEC network mainly includes the communication between the IoT devices and the MEC nodes and between the MEC nodes. First, the terminal equipment can directly communicate with any MEC node. However, IoT devices may not be aware of the existence of the MEC network, which makes the symmetric encryption technology unable to be used to encrypt messages sent by IoT devices. The same is true for the asymmetric key cryptography technology. Second, the MEC nodes involved in multiple paths cannot be fully trusted, so communication between MEC nodes requires end-to-end security.
4) Service placement is an important research direction in MEC, which aims to explore an optimal scheme to improve mobile users' Quality of Service (QoS) [48]. Existing service placement strategies, in particular, are based on the degree to which customers value services. However, the degree of customer preference may involves some sensitive personal information, such as history data, locations, and customized needs. Hence, implementing an effective privacy preservation scheme is a challenging task.

Various edge services put forward new needs for adequate privacy protection. Aside from designing an efficient strategy of preserving privacy information, it is vital to consider how to combine the traditional privacy protection with the characteristics of edge data processing in a diversified service environment. Moreover, if some emerging technologies (e.g., federated learning and blockchain) and edge computing are well-integrated, they can offer great potential for addressing the aforementioned partial challenges concerning security and privacy.

Incorporating Federated Learning Into Edge Computing: In traditional machine learning methods, the training data must be centralized on a single machine or in a cloud center. As a distributed DL technology, federated learning [49], [50], [51], [52], [53] enables users to collaboratively train an algorithm while keeping local data samples on the devices. The various data generated by the user equipment (e.g., wireless channel quality, battery life, and energy consumption) and edge nodes (e.g., computing load, wireless communication quality, and task queue) are utilized as raw training data for model input. Federated learning avoids the privacy leakage problem caused by uploading these sensitive data to the cloud center, only submitting learned model weights to update [54]. In dealing with the challenges of service placement in MEC, federated learning allows users to send the trained results instead of uploading all the users' privacy data, such as preference information, to the cloud center. User privacy information is well protected in this way.

Integration With Blockchain Technology: Blockchain is a distributed ledger technology that does not require centralized control and is protected by the encryption technology [55], [56]. It provides a secure, transparent, and nontamperable platform for network data communication, sharing, and transactions. Furthermore, the blockchain guarantees the automatic execution of predefined rules and terms by intelligent contract technology, and protects data privacy and account security by the asymmetric encryption algorithm.

The blockchain here refers to the ability of network participants to record in the distributed billing system. The core parts of blockchain, such as consensus protocol, ledger topology, and incentives, will be extended in integrated systems to accommodate different levels of edge computing systems and combinations [8]. The integration covers the fundamental layers of blockchain and major capabilities of edge computing, which provides more secure large-scale data storage and effective computing without the need for costly encryption overheads. The blockchain technology can realize security authentication, secure data storage, and secure computing to protect the security and privacy of edge network. On one hand, the blockchain technology allows each user to maintain their own changeable keys, which is convenient for users to offer access and manage data without the involvement of any third parties [8]. On the other hand, coordination on the peer-to-peer basis is allowed by blockchain's pseudonymous property, and metadata (e.g., source, destination, and content) will not be disclosed to anyone.

C. Deployment Issues

There are still many challenges in the deployment of edge computing nodes, such as business selection, investment returns, and operating model. By introducing the microservices technique, the challenge concerning deployment of application packages will be effectively alleviated.

Business needs and scenario selection is the first issue that needs to be considered in the deployment scenario, especially in the 5G era. Whether it is edge computing for individual users in the enhanced mobile broadband (eMBB) scenario, or edge computing for vertical field (e.g., live games, Internet of vehicles [57], [58], and smart manufacturing), deployment needs to fully consider the capacity and the feasibility of the business scenario.

The second is network index and investment returns. The main stakeholder [59] in the edge ecosystem is classified into two categories: 1) infrastructure owners and 2) software developers. The first one usually refers to operators and cloud providers, such as Google Cloud and Amazon Cloud. They are responsible for collecting and storing data, maintaining and managing software and hardware facilities [60]. This business pattern is transparent to users, and subscribers only need to pay for the service without knowing the technical details. The latter mainly includes content providers (CPs) and startups companies. They support the deployment of edge servers, create added-value applications, and help enrich and expand the innovative services. The technology without economic benefits is hard to sustain. In an edge computing system, the maintenance of hardware and software is particularly challenging due to the geographical dispersion of edge nodes. Whether the cloud service provider (SP) or the CP pays for maintenance and management expenses must be considered. Furthermore, it is also necessary to effectively reduce the cost of users' network usage. The closer the computing resources is to the edge of the network, the better experience for users. However, it will leads to the decrease of access users, the reduction of network edge revenue, and the increase of the total cost.

The third is the operating model and management. Infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS) in cloud computing also exist in edge computing. The operators are able to offer different services, such as local offloading services, edge computer room rental, and unified IaaS capabilities when facing various corporate customers. Different with large enterprises, operators provide unified planning and deployment of IaaS and PaaS platforms for small and medium-sized enterprises, which applies to situations where edge nodes are scarce, and the payoff of management is limited [61]. However, the third-party PaaS platform and the management of third-party applications in the edge system need further exploration and improvement.

The fourth is reliability assurance. Protecting the physical environment of edge nodes is also challenging due to the lack of effective measures [62], including data backup, data recovery, and audit measures. Compared with storing data in a stable cloud computing environment, the attackers may modify or delete the user data on the edge node to destroy some evidence. Take the traffic supervision scenario as an example [58], [63], [64], [65]. The high-precision camera on the road records the normal and abnormal conditions, trajectory data, and illegal records of the vehicles. In a traffic accident, these data are the critical evidence to find criminal attacks. The offenders can get away with the law by attacking data on edge nodes. Similarly, household consumption stored in edge nodes and personal health information in electronic medical systems may also become the target of attacks. Moreover, extreme weather conditions (e.g., snowstorms and strong wind) will lead to immeasurable damage of edge data, which is unacceptable for enterprises and customers. The edge nodes also can not provide adequate measures to recover data. When constructing the entire edge system, it is necessary to leverage infrastructures coordination to ensure physical reliability and utilize multiple backup measures to ensure data reliability.

The final one is the deployment issue of application packages. The virtualization technology, such as container, aims at distributing packaged applications as low-overhead VMs to edge servers [66]. However, it is not trivial to decompose monolithic cloud applications into distributed packages and install them into hierarchical IoT system topologies, especially to meet applications' specific demands (e.g., QoS, performance). Therefore, it is necessary to introduce novel programming paradigms that integrate the various aspects of IoT system architecture layers to facilitate distributed software development. Microservices is a promising approach for modularizing applications and services at the process level. A single application is decomposed into noninterfering atomic services in a microservices architecture. Each service unit that performs a specific task, consumes only a tiny amount of computing resources in order to software developers can quickly build it. These units are operated, updated, and deployed independently so that the developer team can carry out the

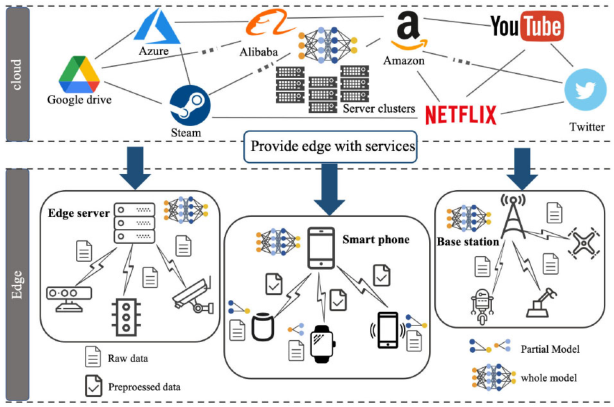

Fig. 2. Overview of edge intelligence.

continuous delivery of functions. The general applications are divided into several small modules and deployed to the edge nodes [11]. Each module can compute, store, and utilize the network resources without affecting other modules. The convergence of distributed IoT and microservices will facilitate package deployment optimization for service delivery and address the deployment challenges of application packages.

IV. Promising Directions

This section will discuss promising directions with the burgeoning of IoE, including emerging technologies, new application scenarios, and the final development form of edge computing.

A. Emerging Technologies

1) Artificial Intelligence: The concept of AI was proposed in 1956. AI refers to the technology that uses algorithms to make machines imitate human thinking to solve problems. So far, outstanding achievements have been widely produced in some fields (e.g., computer vision, natural language processing, and intelligent robots). According to Gartner's prediction, by 2022, more than 80% of enterprises will include AI components in their IoT projects [67]. In particular, as the most important branch of AI, The DL technology has brought the vigorous development of AI applications and services. DL can recognize patterns, detect and analyze abnormal data (e.g., population distribution, air quality, temperature, and humidity) of edge devices, and then send the intelligent analysis results to decision-making applications [68], [69], [70], [71], [72].

In fact, edge computing and AI are progressively merging, mutually benefiting from the realization of edge intelligence, as shown in Fig. 2. Edge computing can provide rich real-time training data and diverse operating environments for AI models [73], [74], [75]. Meanwhile, AI can provide edge computing with powerful learning capabilities. Edge intelligence is projected to move as many DL computations as feasible from the cloud to the edge, enabling a variety of distributed, low-latency, and dependable intelligent services [76]. Moreover, edge intends to integrate DL into the edge to provide dynamic, adaptive edge maintenance and management [4].

To deal with the dynamically changing network environment, emerging learning methods in DL also bring new opportunities to edge intelligence [77]. Take the federated learning as an example. In addition to addressing the privacy challenge of service placement of the MEC network in Section III, the federated learning can also solve the key problem that performance is affected by unbalanced data and harsh communication environment. Moreover, the number of communication rounds required to train the model is reduced by controlling the number of local update steps (increasing the amount of calculation for each user equipment), which shows that the federated learning has a good balance between communication cost and computation cost in the edge network [78]. Lin *et al.* [7] tried to combine federated learning with meta learning. By using a small amount of local data to train a meta model, it is possible to quickly adapt to the task of the target edge node. Transfer learning is also a hot research topic [79], [80], [81], which aims to improve the target task's performance by transferring the existing task's knowledge to the current target task. As the upstream of the machine learning model, transfer learning adapts to multisource heterogeneous data collected on different edge devices through the decoupling model, and the training data and training time requirements of the target field have been significantly reduced. Zhou *et al.* [82] proposed a CNNEF framework that effectively detects abnormal activities in the edge computing environment by using embedded features for transfer learning, which overcomes the limitations of the traditional convolutional neural network (CNN) model. Sufian *et al.* [83] proposed a family health detection edge computing method based on transfer learning. Their work only needs to fine tune a small amount of labeled data to train the model, which can greatly reduce the health crisis caused by the epidemic. More and more methods will be combined with edge computing to make the edge more intelligent. Furthermore, we discussed several other promising research directions about edge intelligence.

1) Accelerate AI services through edge computing. At present, there have been some studies using the DL technology to optimize mobile edge communication systems. However, it is also essential to develop special methods for optimizing learning computing tasks by combining edge computing characteristics with edge devices. For a large number of AI tasks with different priorities and requirements (such as CPU and memory), it is also crucial to find the right collaboration edge node and allocate the appropriate resources. Moreover, game theory algorithms may be applied to edge intelligence to accelerate AI services through edge computing.
2) Improve the edge intelligence efficiency of real-time mobile communication systems toward 5G. In the 5G era, communication links with extremely low latency and high reliability are required. However, general optimization and prediction schemes based on DL require quite a long running time to converge to the result, which is not suitable for mobile edge systems, especially edge computing tasks that require a rapid response at the millisecond level. Edge intelligence

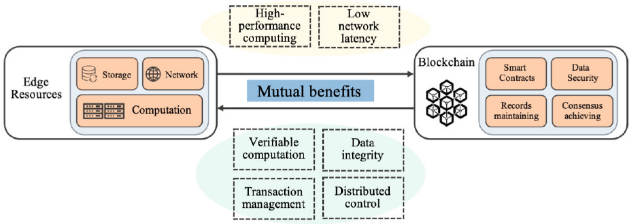

Fig. 3. Common benefits of edge computing and blockchain.

should provide various support for different types of services to eliminate the delays caused by caching, networking, and computing [48].

3) Build the incentive and business model of edge intelligence. The realization of AI services involves three parties: a) mobile operators; b) SPs/CPs; and c) mobile users. The UEs of a small number of mobile users can provide remaining computing resources after meeting their own computing requirements. However, a large number of UEs may depend on the AI computing capabilities of edge nodes and other user devices. In addition, edge nodes spanning multiple mobile operators need to meet the AI computing requirements of SPS and CPS. Therefore, designing a reliable and effective edge intelligence incentive framework holds great promise.

2) Blockchain Technology: The combination of blockchain and edge computing has become an unstoppable trend [84], [85]. In addition to addressing security and privacy issues mentioned in Section III, the convergence also brings some novel opportunities and directions, as shown in Fig. 3.

First, consider the benefits of edge computing for blockchain. The transaction time in blockchain is highly related to the performance and processing power of the server [86], [87]. Some high-performance processors provided by AMD and NVIDIA in the edge computing infrastructure can support the whole transaction. Moreover, in the centralized network architecture, the data stream that blockchain nodes communicate must pass through the whole network before returning. Combining with edge computing can eliminate the need for data traversing the core network and solve the problem of network latency in the blockchain. Then, consider the benefits of blockchain for edge computing. The edge computing infrastructure is still dispersed among telecom operators, which means that application developers will have to interact with each telecom operator to ensure that applications can run between consumers in a country and across borders. The usual solution is to aggregate operators into an entity, such as cloud SPs, such as AWS and Azure, with a unified control interface in the public cloud field, so as to monopolize the cloud service market [88]. Instead, the blockchain technology may be utilized to build a decentralized edge computing marketplace that connects suppliers of edge infrastructure with those in need, without relying on a single point of control.

The distributed architecture makes edge computing challenging to manage HetNets. By building distributed control on edge nodes, blockchain ensures the correctness, consistency, and validity of edge data and regulations throughout their life cycle. This can effectively solve the mobility problem between heterogeneous nodes located at the edge of the network. Moreover, the scattered data in the edge network is more likely to be lost or stored incorrectly. The transaction management provided by the blockchain has potential to address this challenge. For example, the record of edge data becomes unchangeable once it is stored on the transaction ledger. In this context, edge devices can perform large-scale computing or collaboration in an untrusted network environment [89]. The blockchain technology also provides transaction transparency and data integrity for the edge network, and allows the replication of publicly verified data records across edge nodes [90]. Moreover, issues, such as network congestion, link failure, and privacy leakage may occur in the data interaction and service migration between heterogeneous devices and edge servers due to illegal attacks. The solution to this issue is to add the block mining process to each edge device, verify the data transaction, and protect and connect through the immutable ledger to improve the security of the edge network.

In current cloud-based blockchain services, Microsoft provides blockchain as a service based on the Azure cloud platform, and cloud-hashing in the U.K. offers Bitcoin mining services to users who purchase services online. The entire process does not require users to install and deploy any equipments. Other companies, such as IBM, Google, and Oracle integrate blockchain ledger into their business-level cloud services. The blockchain transaction economic model based on edge computing is missing and will be the focus of future research.

3) 6G: The deployment and comprehensive promotion of 5G have brought the world the ultimate user experience of mobile Internet, and communication capabilities and service quality have been improved by leaps and bounds. However, the next ten years will transition from industry 4.0 to industry X.0. 5G cannot cope with application scenarios requiring microseconds and Tps levels, such as holographic remote transmission, remote surgery, and extended reality (XR). As the next generation of the revolutionary communication technology, 6G wireless network will support a transmission rate of TB per second and a significantly low transmission delay. The speed is 50 times that of 5G network and the delay is half that of 5G network.

The development of 6G will continue to accelerate the evolution from the IoT to the IIoT. When data are transferred from cloud servers to edge devices, 6G provides functions, such as high-speed security, ultrahigh reliability, and ultralow latency, which greatly reduces data loss rate and bit error rate and ensures seamless data connection between edge devices [91]. Consider the unmanned aerial vehicle (UAV) system under COVID-19 pandemic. To deal with the epidemic situation, various data, such as the image, digital, CT scanning, and other data obtained by the UAV will be directly sent to the edge server for processing. The edge will train the AI model to accelerate the processing and data analysis and then send results to relevant government departments. All devices are connected via 4G networks in this process, and the transmission rate is slow, only 100 Mb/s. Even 5G networks with speeds of up to 20 Gb/s cannot meet the needs of

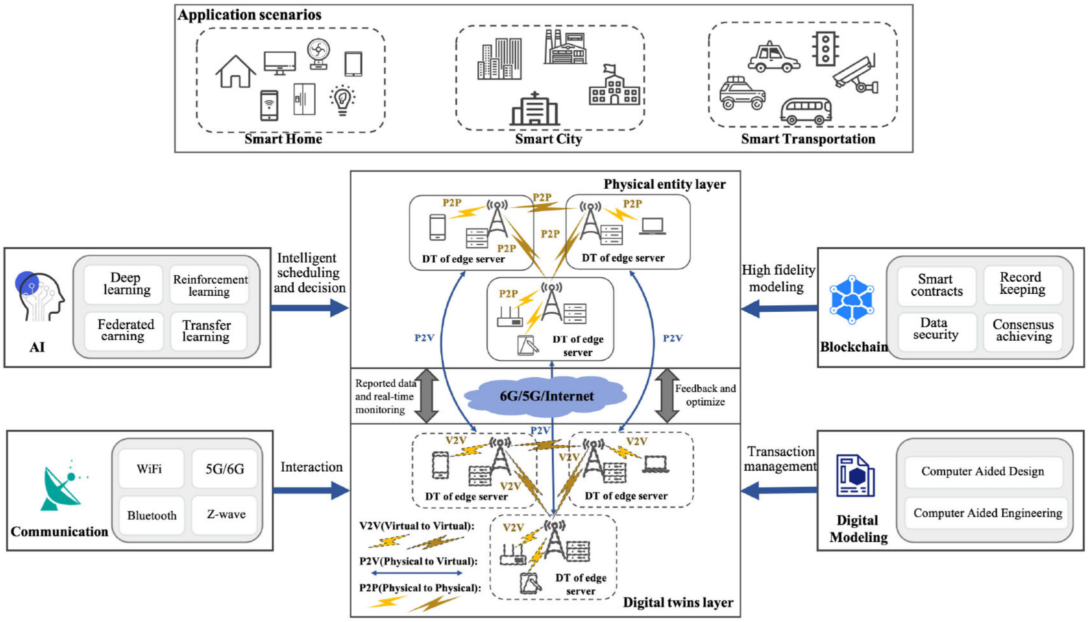

Fig. 4. DT framework.

future emergencies. For example, the deterioration of critical patients requires immediate feedback. The social distance and isolated persons in the floating population also need to be monitored in real time. In these critical scenarios, 6G can provide a microsecond response [92] to deal with challenges. Meanwhile, the deployment of edge computing in the 6G network will improve the system performance, realize the core network traffic optimization, and provide a novel network service. Furthermore, compared with cloud SPs, such as Amazon and Google, operators in edge computing systems will have more advantages in computing and communication resources, which allows them to regain their market position and increase the added value of their services in 6G era.

4) Digital Twin: The DT originated from the NASA project of the U.S. Department of Defense, which is utilized to maintain and guarantee the health of aerospace vehicles by the virtualization technology. It makes full use of various physical models and combines sensor data, algorithms, and decision analysis to realize real-time virtual mapping of the physical world on the information platform, thereby reflecting the entire life cycle of the corresponding physical entity [93], [94]. A series of enabling technologies (e.g., AI, blockchain, and 6G) drive DTs to support some application scenarios, such as smart home, smart city, and smart transportation. Fig. 4 shows the applications of DTs. The DT network (DTN) [31] is a network of many-to-many mappings formed from many one-to-one DTs, which aims to enable the dynamic interaction and coordinated evolution of a large number of physical and virtual objects. By linking several DT nodes in DTN, physical objects and virtual twins are able to interact, cooperate, exchange information, perform activities, and establish an information-sharing network.

Physical to physical (P2P) and physical to virtual (P2V) communication in DTN network require ultralow sensor delay, data processing delay, and feedback delay in some time-sensitive application scenarios, such as medication control and remote surgery. The convergence with edge computing is empowered to alleviate this issue. The cloud–edge–end framework offloads the computing tasks of the twin terminal to the edge network, which mainly solves the device's shortcomings in terms of resource storage, computing performance, and energy efficiency. Cooperative cloud–edge–end computing is able to provide DTN with low-latency computation, increased computational ability with constrained resources, and continuous update. Processing and analyzing closer to the edge will reduce the communication delay of mutual mapping in physical space and virtual space. DTs systems based on edge deployment will have greater flexibility in defining, developing, and utilizing real-time IoT systems.

B. New Application Scenarios

The emergence of edge computing paradigm has supported the new application scenarios, including remote-working, the physical retail industry, and digital advertising.

1) *Working in Post-Epidemic Era:* The outbreak of COVID-19 has had a profound impact on the way we live and the operating model of human society [95]. It will not be resolved fast and will continue for a long time. Around 300 million people have been infected with coronavirus worldwide to date, with over 4 million deaths. Not only human beings, but all walks of life are also experiencing unprecedented tests. The weaknesses of the Internet architecture that we rely on every day are completely exposed under epidemic. Enterprises must also respond to the ever-changing business world and promote the long-term transition to intelligent edge computing solutions to cope with the post-epidemic era. First, significant changes have taken place in the way employees work. We call it the "remote revolution."

Remote collaboration and home office have become the norm. Both consumers and companies are looking for positive ways to meet office requirements during the quarantine period. Most of the virtual desktop infrastructure (VDI) hosted in the cloud allows any device to access it at any time. However, the VDI architecture has some shortcomings, including high construction cost and over-reliance on network environment. By introducing some implementation schemes of the edge computing architecture, such as intelligent desktop virtualization (IDV) and virtual OS infrastructure (VOI), employees may more efficiently utilize their devices at home, resulting in cost savings, less hardware needs, and more flexible operation [96]. Different from VDI, which concentrates all desktop computing resources in the data center and sends interfaces to terminal devices, edge computing takes a more decentralized approach to meeting operational technological requirements while simplifying administration and deployment functions. Edge computing solutions enable IT to manage and protect desktop images and devices while maintaining high performance, mobility, and flexibility for users. Thanks to the rapid development of edge computing paradigm, organizations may rapidly and inexpensively introduce desktop virtualization without investing in infrastructure.

2) *Physical Retail Industry:* Edge computing shows extraordinary marketing potential in user personalization and in-depth positioning and provides users with an unprecedented digital product experience. In order to meet social distancing requirements and comply with epidemic prevention policies, the physical retail industry has been hit like never before. It is undergoing a transformation to survive and compete with the online retail industry. The ways of self-help include building a real-time supply chain, forming a fully automatic manufacturing chain, and providing customers with a personalized shopping experience. By deploying edge computing systems, brick-and-mortar retailers [97] are committed to enabling customers to seamlessly transition from the physical to the digital experience via new channel technology. The store may offer a virtual reality experience to attract additional consumers, as well as real-time inventory data presented on touch displays. Moreover, if a customer does not have a favorite product, the system will intelligently recommend other products based on the historical preferences of this customer. All data will no longer simply pass through the edge but will continue to integrate existing data to track target users in order to improve user experience. In addition to providing users with a better shopping experience, edge-based systems cases will include smart shelves with dynamic pricing, digital signage, and more. Additionally, the edge computing technology enhances the offline experience of the store, which continues to operate even when the Internet is down or the main

3) *Digital Advertising:* The data processing model combined with edge computing can accelerate data-driven advertising decisions and decrease users' time for advertising, which has made a huge contribution to digital advertising such as video advertising [98], [99]. In other cases, edge computing will make the processing power available on consumer devices grow, and data will be processed on the user device itself. We have seen edge computing used to enhance user privacy. Edge computing can keep the user's data from leaving the local device, and the user's local device can use personal data to make advertising decisions, which enables third parties to accurately place advertisements without directly obtaining the data. Edge computing enhances the privacy of Internet advertising by minimizing the amount of data transmitted by consumer devices.

C. Trends

While edge computing has facilitated several advances and displayed amazing promise, it is still a long way from achieving its final form. Edge computing will finally transform into "edgeless computing." Edgeless indicates that the edge will collaborate with itself and interact with other devices directly rather than via the cloud. Specifically, the cloud–edge–end architecture will abandon the cloud level and eliminate the need for computing in the cloud center. The terminal equipment will have the strong computational power and the ability to handle large amounts of data. Take the smart wearable device (such as Apple watch) as an example. The smart watch is capable of monitoring the user's nighttime sleep quality. The device gathers different data (e.g., depth and light sleep duration, heart rate fluctuations, and blood oxygen content), uploads them to a central server for extensive analysis, and then, presents the user's sleep quality findings and makes recommendations for future sleep adjustments. However, if the smart watch uses its computational capacity to do a full analysis and then, directly provides the user with a sleep report, the efficiency will be higher without the involvement of the cloud. The data processing takes place entirely within the terminal device, and it is no longer necessary to go back into the cloud. In this context, the cloud server may function as a data repository, and the edge nodes will also have their tiny databases, rather than relying on the cloud. The more dispersed the edge devices are the more flexible the network is and the less traffic it carries. The vision that can be handled quickly anywhere will surely be realized in the future.

V. Conclusion

Today, edge computing is one of the most effective solutions to address some challenges associated with enormous volumes of data that various industries generate and consume every day. In this work, we have described the brief overview of edge computing; discussed the main existing challenges in edge computing and novel solutions supported by emerging technologies; and explored the possibility of technologies integration, finally, discussed several new applications scenarios and proposed the final form of edge computing. We believe that the future of edge computing lies in the organic integration with emerging technologies. Convergence will transform manufacturing and services, create actionable business intelligence, and develop flexible business ecosystems.

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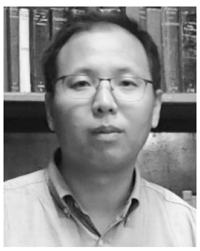

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