Applications of Auction and Mechanism Design in Edge Computing: A Survey

Houming Qiu, Kun Zhu, *Member, IEEE*, Nguyen Cong Luong, Changyan Yi, *Member, IEEE*, Dusit Niyato, *Fellow, IEEE*, and Dong In Kim, *Fellow, IEEE*

***Abstract*—Edge computing as a promising technology provides lower latency, more efficient transmission, and faster speed of data processing since the edge servers are closer to the user devices. Each edge server with limited resources can offload latency-sensitive and computation-intensive tasks from nearby user devices. However, edge computing faces challenges such as resource allocation, energy consumption, security and privacy issues, etc. Auction mechanisms can well characterize bidirectional interactions between edge servers and user devices under the above constraints in edge computing. As demonstrated by the existing works, auction and mechanism design approaches are outstanding on achieving optimal allocation strategy while guaranteeing mutual satisfaction among edge servers and user devices, especially for scenarios with scarce resources. In this paper, we introduce a comprehensive survey of recent researches that apply auction approaches in edge computing. Firstly, a brief overview of edge computing including three common edge computing paradigms, i.e., cloudlet, fog computing and mobile edge computing, is presented. Then, we introduce fundamentals and backgrounds of auction schemes commonly used in edge computing systems. After then, a comprehensive survey of applications of auction-based approaches applied for edge computing is provided, which is categorized by different auction approaches. Finally, several open challenges and promising research directions are discussed.**

***Index Terms*—Auction, edge computing, cloudlet, fog computing, mobile edge computing, resource allocation, computing offloading, incentive, IoT, blockchain.**

Manuscript received March 18, 2021; revised July 19, 2021, October 9, 2021, and December 20, 2021; accepted January 19, 2022. Date of publication January 28, 2022; date of current version June 9, 2022. This work was supported in part by National Natural Science Foundation of China (Grant No. 62071230, 62061146002, and 62002164), and in part by Natural Science Foundation of Jiangsu Province (Grant No. BK20211567). The associate editor coordinating the review of this article and approving it for publication was X. Chen. *(Corresponding author: Kun Zhu.)*

Houming Qiu, Kun Zhu, and Changyan Yi are with the College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China (e-mail: hmqiu56@nuaa.edu.cn; zhukun@nuaa.edu.cn; changyan.yi@nuaa.edu.cn).

Nguyen Cong Luong is with the Faculty of Computer Science, Phenikaa University, Hanoi 12116, Vietnam (e-mail: luong.nguyencong@phenikaa-uni.edu.vn).

Dusit Niyato is with the School of Computer Science and Engineering, Nanyang Technological University, Singapore 639798 (e-mail: dniyato@ntu.edu.sg).

Dong In Kim is with the Department of Electrical and Computer Engineering, Sungkyunkwan University, Suwon 16419, South Korea (e-mail: dikim@skku.ac.kr).

Digital Object Identifier 10.1109/TCCN.2022.3147196

I. INTRODUCTION

WITH the rapid development of big data, Internet of Things (IoT) [1], artificial intelligence (AI) [2], 5G and other intellectual technologies, massive amounts of data and service requests will be generated at the end devices [3]. According to the recent report from Gartner, more than half of the enterprise data will be generated in the edge of the network rather than the traditional data center (e.g., cloud platform) by 2022. Cloud computing (CC) as a centralized computing paradigm offers services for end users by migrating data, computation, and storage to the remote cloud data center. However, massive long-distance data transmission will inevitably cause delay and network congestion [4]. It indicates that CC cannot meet the increasing requirements for low latency and high quality of experience (QoE) application scenarios, especially in Internet of Vehicles (IoV) [5], intelligent networks [6], telemedicine [7], smart city [8], AR/VR [9], etc.

The emerging edge computing (EC) provides an effective solution to overcome the limitations of the cloud. Different from CC, EC is a type of decentralized computing paradigm, which moves data, computation, and storage from the data center to edge nodes of the network [10]. Therefore, EC can bring faster speed of data processing, more efficient transmission, and lower latency since the edge nodes are closer to the user devices. In addition, EC also provides more intelligent analysis and processing services near the data sources, e.g., user equipments (UEs), intelligent vehicles, etc. In this case, the communication delay can be significantly reduced, the system efficiency can be effectively increased, and security and privacy of data can also be significantly reinforced [11]. In recent reports, the global market size of EC has reached at \$3.5 billion in 2019, and exhibiting a compound annual growth rate exceeding 37% from 2020 to 2027 [12].

Despite of possessing several advantages, EC raises big issues of resource management. In particular, edge nodes in EC typically have limited resources, i.e., computing, storage, and network resources, while end users, i.e., service requesters (SRs), have a rapid growth of computing demands. Thus, one issue is how to efficiently allocate the resources to the SRs. In addition, EC introduces more service providers (SPs) in the computing market. Since both SPs and SRs are naturally selfish [13], how to motivate both the SPs and SRs to participate in the market is another issue. On the other hand, it is also crucial to fairly allocate limited resources to SRs while meeting heterogeneous demands of them.

TABLE I
SUMMARY OF COMMON USED IN THIS PAPER

Acronym	Definition
BB	Budget balance
CE	Computational efficiency
EE	Economic efficiency
EC	Edge computing
ECS	Edge computing server
FC	Fog computing
FCN	Fog computing node
IR	Individual rationality
IC	Incentive compatibility
MEC	Mobile edge computing
MDs	Mobile devices
MUs	Mobile users
QoS	Quality of server
QoE	Quality of experience
SRs	Service requesters
SPs	Service providers
TF	Truthfulness
UEs	User equipments

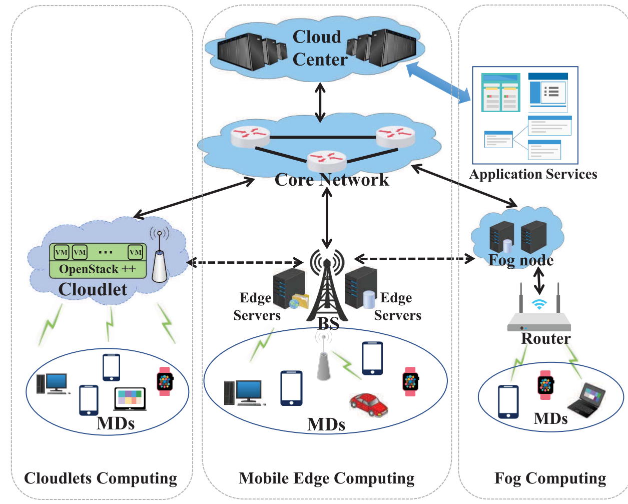


Fig. 1. The system architecture of EC, include three main paradigms, i.e., cloudlet, MEC and FC.

To address such issues, auction theory [14] as a popular economic approach has been widely applied, e.g., in wireless networks [15]. Specifically, auction-based mechanisms are promising since they can fairly and efficiently allocate limited resources of sellers to buyers in a trading form at competitive prices. An ideal auction-based mechanism should ensure several desirable properties, e.g., truthfulness (TF), budget balance (BB), individual rationality (IR), and economic efficiency (EE) [16]. In particular, with the EE, the auction-based mechanisms guarantee that the resources are allocated to the buyers that value them the most. Given those advantages of auction theory, several works [17], [18] have recently adopted auction theory to solve the resource management in EC. It is inspired from the existing works that different types of auction methods are suitable for different types of problems in specific application scenarios.

Although there are surveys related to EC such as [11], [19]–[21], they do not focus on auction approaches. Also, there is one survey related to auction theory, i.e., [22], but it does not focus on EC. To the best of our knowledge, there is no survey specifically discussing the use of auction theory, an emerging approach, for EC. This motivates us to deliver the survey with the comprehensive literature review on the auction and mechanism design approaches in EC.

The rest of this paper has the following organization. In Section II, we present a brief overview of EC and the comparison of cloudlet, fog computing (FC), and mobile edge computing (MEC). Section III gives a review of auction theory. Section IV presents the applications of auction approaches for EC. Section V highlights open challenges and future research directions of utilizing auction approaches to EC. Finally, Section VI concludes for this paper.

Some important definitions of the acronyms that will be frequently used are summarized in Table I.

II. Fundamentals of Edge Computing

In this section, we first give an overview of EC, including three main types of computing architectures, i.e., cloudlets, FC, and MEC. Then, we present the comparison of cloudlet, FC, and MEC, and discuss the advantages and disadvantages of each computing architecture. After then, some popular application scenarios of EC are briefly introduced. Finally, we detailedly discuss the advantages of blockchain using in EC.

A. Main Paradigms of Edge Computing

As an emerging computing framework, EC has been attracting great attentions because it can provide ultra-low-latency services for end devices. As illustrated in Fig. 1, the system architecture of EC includes three different paradigms, i.e., cloudlet, FC, and MEC. In the following subsections, we will give a brief overview of each computing paradigm.

1) Cloudlet Computing: Cloudlet [23] is a computing architecture combining both mobile computing and CC. Enlightened by the definition in [23], cloudlet is a trusted cluster of computers that provides cloud services at the edge of the network. As shown in Fig. 1, the cloudlet acts as the middle layer in the three-tier architecture, i.e., mobile devices (MDs), cloudlets and the cloud. A cloudlet can usually be regarded as a micro data center, deployed near mobile devices to support offloading and caching. Furthermore, the ideal location of the cloudlet is at the edge of the network which can offer an one-hop access with high bandwidth for MDs. Through cloudlets, MDs can offload latency-sensitive or computing-intensive applications to achieve shorter latency and less system overhead. Obviously, the cloudlet enhances the capability of mobile cloud computing (MCC) [24] in addressing the latency challenge between MDs and the cloud.

2) Fog Computing: As a decentralized computing architecture, FC was introduced by CISCO in 2012 [25]. Similar to MEC, the main idea of FC is to migrate large-scale processing tasks from the CC center to edge servers that are close to end devices [26]. However, FC is also a novel computing architecture due to filling the gap in providing location awareness and real-time response for IoT systems. Hence, FC is more suitable for IoT systems. In FC, a set of medium-sized computing units gathering as fog layers are placed between edge devices and the cloud, where a single computing unit is defined as a fog computing node (FCN). Generally, an FCN can provide a set of medium-sized services, (e.g., computing, storage, networking) to edge devices [27]. It is worth noting that the above FCNs are along the routing path. As large-scale processing tasks are mostly carried out in FCNs, the latency of task processing and the network transmission load are greatly reduced. Due to the locality of FC, end devices can obtain various benefits such as real-time transmission of data, pre-analysis of data source, etc. Recently, the decentralized architecture of FC also faces security and privacy leakage issues [28], [29]. A general system architecture of FC is described in Fig. 1.

3) Mobile Edge Computing: In 2014, European Telecommunications Standards Institute (ETSI) first proposed the concept of MEC [30], the system architecture of MEC is illustrated in Fig. 1. They suggest deploying sufficient computing capacity, storage space and service environments to the edge network within the radio access network (RAN). The main idea of MEC is to distribute highly complex and heavy computation tasks to adjoining edge servers, providing ultra-low-latency computing services, higher bandwidth for transmission, less consumption for energy [18], [31], [32], etc. Thus, the workload of end users can be greatly alleviated by offloading highly complex and computing-intensive tasks to edge nodes rapidly. Moreover, the battery lifetime and storage space of user devices, e.g., industrial Internet of Things (IIoT) devices, can be significantly prolonged and expanded, respectively. Therefore, user devices can run various latency-sensitive or computing-intensive applications such as unmanned aerial vehicles [33], smart city [8], AR/VR [9], etc. It is noteworthy that context-awareness, as a key feature of MEC, can promote and improve context-aware services for user devices. Due to the low concentration and small-scale of data resources of subscribers, the probability of being attacked is much smaller for edge servers in the MEC. In addition, many MEC servers are equipped with identity authentication, intrusion detection and data encryption which can effectively address the security-and-privacy issues [34], [35]. It indicates that the applications with privacy-sensitive and security-sensitive can be well supported by MEC and greatly benefit from MEC. Given the aforementioned advantages, it is no doubt that MEC eliminates the drawbacks of FC and MCC. With the vigorous development of IoT, more applications will be supported by MEC [36].

B. Comparison of Cloudlet, FC and MEC

EC paradigm generally contains three different representation forms, i.e., cloudlets [23], FC [25], and MEC [37]. It is obvious that all of them have the identical idea, i.e., migrating computing resources and services from the central node to the edge nodes of networks. Nevertheless, learning from [38] and [39], there are also some differences between them that can be summarized in Table II.

TABLE II
COMPARISON OF CLOUDLET, FC AND MEC

Paradigms	Location for Computation	Proximity	Internode Communica-tion	Context Aware-ness
Cloudlet	Local/Nearby Servers	One Hop	Partial	Low
FC	Servers along the Routing Path	One/Multiple Hops	Full	Medium
MEC	BS and Adjoining Servers	One Hop	Partial	High

Although cloudlets, FC, and MEC utilize edge servers to provide various services for end devices, the location of the edge servers are exceedingly different. The location of computing for cloudlets, FC, and MEC are adjoining servers, servers along the routing path, and base stations (BSs) and adjoining servers, respectively. In FC, unlike cloudlets and MEC, the end devices may need many hops to find a resourceful FCN. Thus, FC has the most comprehensive inter-node communication support. MEC and cloudlets only have partial inter-node communication support [40]. It is noteworthy that MEC has the highest context awareness as a result of obtaining detailed information of end users, e.g., location and network load. FC is worse than MEC in context-awareness owing to the limited view of the network devices, e.g., routers, switches, etc. Fortunately, the context-awareness of FC can be effectively improved by the strong capability of inter-node communication. Furthermore, the standalone architecture of cloudlets leads to the lowest context-awareness because the devices connected to the cloud are independent of each other [38]. Regarding to the computing time, MEC and cloudlets can be able to respond to assigned tasks timely due to the allocation strategy and the virtualized property of resources, while the legacy devices used in FC usually have poor processing and storage capacity which may prolong the computing time.

Although EC is an efficient solution for processing computing intensive and latency-sensitive tasks of edge devices, the limited resources of edge servers restrict its application and development. As a popular trading form, auction can efficiently allocate resources while satisfying the heterogeneous requirements of both SPs and SRs [41]. Thus, it has attracted a lot of research interests recently.

C. Popular Application Scenarios of EC

EC as a promising computing paradigm has been widely applied in IoT, IIoT and IoV since it can provide services for processing computing-intensive and latency-sensitive tasks. Next, we briefly introduce these application scenarios.

1) IoT: IoT is a promising technology paradigm that connects a large quantity of smart devices through the Internet, in which smart devices can communication with each other. The users can monitor real-time data of IoT devices and timely control them remotely [42]. However, the IoT devices is hindered by scarce computing resources, short battery life, low network bandwidth, etc. EC as an effective solution can enhance the capability of IoT devices and overcome their limitation [43]–[46].

2) IIoT: Similar to IoT, IIoT is a subset of IoT which combines industrial management systems with intelligent machines, intelligent instruments, sensors, actuators and controllers through the Internet. In fact, it is a deep-level fusion of Internet technique and industrial systems. Hence, IIoT can further enhance production efficiency of industrial systems. However, the application of IIoT also face with some challenges, such as high requirements of real-time control, security and privacy of devices and a huge amount of local data to process. Fortunately, EC is suitable for IIoT to address those challenges [47], [48].

3) IoV: IoV as the cornerstone of the up-and-coming intelligent city, constructs an interconnected transportation system to provide intelligence-aided vehicular services [49]. IoV can effectively improve the driving environments with respect to safety, comfort and convenience, by collecting, processing and analyzing massive neighboring traffic information. However, many computing-intensive and latency-sensitive traffic applications cannot be supported by a single vehicle with poor computing capability and scarce resources. Inspired by the EC paradigm, the above issues can be well-solved by offloading the resource-hungry and latency-sensitives applications to nearby service nodes [5], [50].

D. Blockchain for EC

As a decentralized, transparent and tamper-resistant ledger system based on a peer-to-peer (P2P) network, blockchain has gained unparalleled attention recently. Decentralization, security, transparency, immutability, and anonymity are the key properties that enable blockchain to achieve outstanding ability on address various issues of privacy and security [51]. It has been applied to many application scenarios, such as IoT, smart city, healthcare, etc.

On the one hand, EC has received ever-increasing attention and widespread application due to it distributes a large quantity of computation and storage from CC to the edge of network that close to end devices [41]. Numerous computing nodes provides computing services for end devices to address the complex and delay-sensitive applications. Although the distributed architecture of EC drastically benefits the edge network, it still faces critical challenges of security and privacy. In EC, the data are divided into multiple sub-data-blocks and assigned to many nearby computing nodes which may lead to partial data loss. Hence, data integrity cannot be fully ensured in EC. Furthermore, it is inevitable to suffer from data leakage, information tampering and other privacy or security issues when the data are stored in malicious nodes. Fortunately, the crucial issues of data integrity, security and privacy can be effectively solved by blockchain technology. 1) data integrity can be guaranteed by using cryptographic techniques, such as merkel tree. 2) In a blockchain, the reliability and consistency of the data are maintained by some consensus algorithms, such as Proof-of-Work (PoW). 3) The privacy preservation issues can also be solved by achieving true anonymity. Therefore, applying blockchain to EC is extremely perfect for the significant improvement of data integrity, reliability, security and privacy [20], [52], [53].

On the other hand, EC can provide abundant computing services for blockchain network that deployed in the edge of the network. It is well-known that end devices with limited computing resources cannot support running a blockchain due to the resource-hungry applications, e.g., solving PoW puzzle. In EC, by offloading the resource-hungry applications to the edge servers, the end devices can participate in blockchain and benefit from it. Thus, EC can expand the scope of application for blockchain, and effectively improve the scalability of it.

In summary, blockchain and EC complement each other quite well. It is a natural trend to combine EC with blockchain that can completely overcome their own challenges and limitations [54].

III. Overview of Auction Theory

Due to many advantages of auction theory, it has widely been applied to both economics and engineering areas. In this section, we first discuss the reasons for using auction approaches for resource allocation in EC. Then, we introduce the basic terminologies of auction theory. After that, some popular auction methods are briefly discussed.

A. Basic Terminologies

1) Seller: A seller refers to the owner of the auction commodities or services, and wants to sell them at certain prices for gaining maximum profit. In the EC market, edge servers usually act as the sellers which own a number of commodities, such as computing and storage resources, network bandwidths, etc.

2) Bidder: A bidder is a buyer who wants to purchase commodities or services from sellers. In the EC market, UEs and MDs usually act as buyers that want to purchase diverse resources (e.g., computing resource) to process computing-intensive and latency-sensitive tasks. Both bidders and sellers are auction participants.

3) Auctioneer: An auctioneer typically plays the role of an executor to implement auction algorithm, and determines the winners and payments according to the auction rules for both buyers and sellers. In the EC market, the auctioneer can be a service provider (a seller) or a trusted third party.

4) Commodity: In an auction, a commodity refers to a trading object between a seller and a buyer. Sellers sell a commodity with a value at an optimal price through the competition across the buyers. In the EC market, the commodities can be computing resources, cache resources, or network resources.

5) Price: In general, the price emerged in the form of competition during an auction process. It may be an asking price, i.e., the price that a seller agrees to sell the commodity, a bidding price, i.e., the price that a buyer agrees to pay for the commodity, or a hammer price (transaction price), i.e., a final trading price in the auction.

B. Motivation of Using Auctions in EC

In popular application scenarios of EC, such as IoT, IIoT and IoV, edge servers provide their computing services for end devices to process many computing-intensive tasks. However, the computing services at edge servers are limited compared with the massive demands from the ever-increasing edge devices. In order to complete many computing-intensive tasks, end devices need to compete with each other for scarce computing services of edge servers within their proximity.

As aforementioned, the competitive relationship among many end devices for limited resource from edge servers just like sellers and buyers in a market. Thus, it is suitable to apply economic model to describe the problem of resources allocation in such a EC market. Auction approaches as the well-known market-based allocation strategies can achieve excellent performance on allocation and economic efficiency for resource allocation [14]. From the perspective of mechanism design, auction-based mechanisms generally can be divided into two aspects. One is optimal mechanism, which focus on maximizing the profit of sellers. The resource owners are stimulated to participate in resource trading. The other one is efficiency mechanism, which focus on maximizing social welfare, i.e., maximizing the sum of the utilities of buyers and sellers. It indicates that the resources are allocated to the buyers that value them the most after an auction process has accomplished. In an auction, bidders bid against each other and sellers sell the commodities to the highest bidder to gain more profit. We can see that auction mechanisms utilizes a market competition environment to allocate resources to the bidder with the highest valuation. It is quite consistent with individual pursuit for fair service allocation.

On the other hand, an auction can be characterized by four properties, i.e., IR, BB, TF and EE. More specifically,

1) IR: Each trading participant will not lose their utility when the auction is done, i.e., $\mathcal{U}_{b,j} \geq 0$, $\mathcal{U}_{s,i} \geq 0$ for $\forall i \in \mathcal{M}$, $\forall j \in \mathcal{N}$, where $\mathcal{U}_{b,j}$ and $\mathcal{U}_{s,i}$ denote the utility of *j*th buyer and *i*th seller, respectively.

2) BB Includes Two Sides:

- *Strong BB:* All monetary transfers should be limited between buyers and buyers and the auctioneer cannot lose/gain money.
- *Weakly BB:* When the trade is done, the revenue of the auctioneer is non-negative.

3) TF: The submitted bids/asks of buyers/sellers are both based on their true valuations. Each of them cannot improve its utility by submitting a untruthful bid/ask.

4) EE: The overall utilities of the trading participants will be the best when the auction is complete.

Obviously, an auction-based allocation mechanism satisfies these properties (not all) can certainly ensure fairness and efficiency for services allocation. Specifically, IR ensures the utilities of buyers and sellers are nonnegative, which motivates them to participate in the auction. BB ensures the fairness and credibility of the auction mechanism. TF ensures that no buyers or sellers cheat or cheat in the auction and they should report the true values or valuations. It is absolutely vital to the perceived fairness of auctions [55]. EE ensures the commodities are allocated to the buyers that value them the most. Thus, the above properties in essence guarantee fairness and efficiency of auction-based mechanisms for resource allocation. More detailed research about using auction approaches in EC can be seen in Section IV.

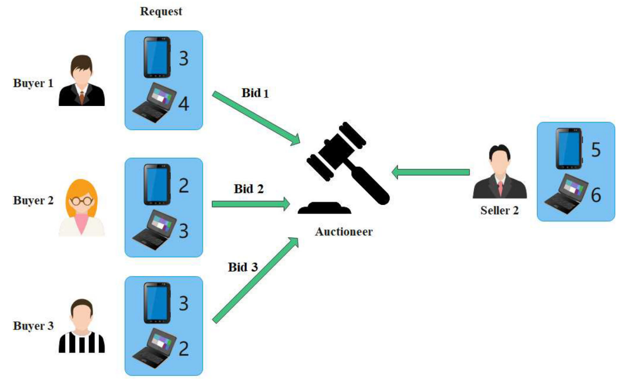


Fig. 2. The combinatorial auction model.

C. Auction Approaches Commonly Used for Edge Computing

To the best of our knowledge, different types of auction approaches are suitable for addressing different types of problems in practical scenarios. Specifically, double auctions with many-to-many structure are popularly used for solving allocation issues over multi-user and multi-server competition scenarios in EC [56]. Combinatorial auctions are outstanding on trading a package of commodities which belong to different types but complement each other. Online auctions overcome the limitation of time and space for auctions, the auction requests can be timely handled over the Internet. As a type of buyer-side auction, reverse auctions are suitable for some EC markets that require less procurement costs [57]. Hierarchical auctions are quite suitable for addressing resource allocation issues with obvious hierarchical structure, and they are coupling with each other [58]. Revenue-optimal auctions are usually exploited in designing incentive mechanisms to improve resource utilization [59]. We summarize the above auction approaches along with their application scenarios for resource allocation in EC in Table III.

Next, due to the popularity of combinatorial auction, double auction, online auction, reverse auction and hierarchical auction, they are introduced in the following.

1) Combinatorial Auction: A combinatorial auction [60] is an auction, in which each bidder bids for a combination of various commodities. Compared with the traditional auction methods, buyers can obtain a package of combinatorial commodities which contain different types of commodities.

In the combinatorial auction, each buyer submits a bid to the auctioneer that indicates the demand of a bundle of commodities rather than a single commodity. After collecting bids/asks submitted by buyers/sellers, the auctioneer gives an optimal allocation scheme over buyers. Fig. 2 describes the use of combinatorial auction for computing resource allocation in an EC market. The market includes 3 buyers, i.e., bidders, and one seller, i.e., the auctioneer. Buyers submit their bids to the seller that specify the demands of computing resources. In particular, each bid indicates the demand of CPU resources and energy resources. Then, the problem is to determine the winners and the price that each winner needs to pay. To solve this problem, some optimization algorithms can be applied,

TABLE III
SUMMARY OF POPULAR AUCTION APPROACHES AND FEATURES

Auction Type	features and Descriptions	Suitable Scenarios
Combinatorial	• Auction commodities with heterogeneity • Certain combinations of commodities are valued most	• Buyers compete for multiple different but related commodities • Type: e.g., network bandwidth allocation
Double	• Multiple sellers and multiple buyers • Sellers and buyers submit their asks and bids respectively	• The number of sellers and buyers are more than one • Type: e.g., resource/task allocation, resource sharing
Online	• The auction process is conducted on the Internet • Most auction websites act as auctioneers	• Buyers and sellers suffer from time and space constraints • Buyers and sellers require a convenient and free auction process • Type: e.g., resource/task allocation, resource sharing
Reverse	• A buyer-side auction and is beneficial for buyers • Sellers compete to obtain business from the buyer	• Buyers want to save cost • Price is treated as a key properties • Type: e.g., resource/task allocation, resource sharing
Hierarchical	• Obvious hierarchical structure • Each layer is coupled to each other	• The resource/service allocation issue have obvious hierarchical structure • Type: e.g., resource/task allocation, resource sharing

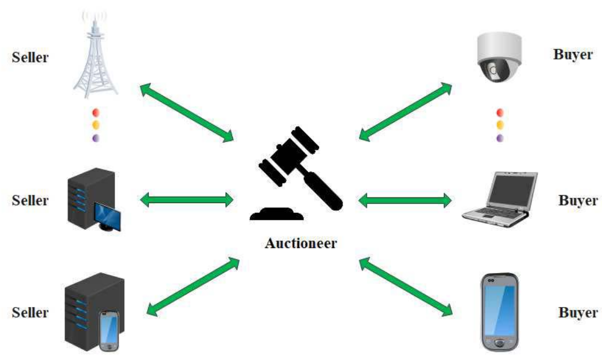


Fig. 3. The typical many-to-many structure of double auction.

e.g., dynamic programming (DP), greedy algorithm and graph neural networks [61].

It is obvious that the combinatorial auction is appropriate to trade a bundle of complementary commodities and can effectively improve auction efficiency of allocating multiple commodities combination.

2) Double Auction: A double auction [62] is a multi-item auction that is widely applied to deal with optimal allocation problems. Different from conventional auctions (e.g., English auction [14], Dutch auction [14], first-price sealed-bid auction and second-price sealed-bid auction [16]), double auction is not a one-to-many structure, but a many-to-many structure, i.e., the number of sellers and buyers are both more than one, as depicted in Fig. 3. In the double auction, sellers and buyers respectively submit their asks and bids to an auctioneer, i.e., an executor of the auction process. Then, the auctioneer sorts asks (asking prices) and bids (bidding prices) in descending order and ascending order, respectively. After that, the auctioneer calculates the transaction price p^*, i.e., a hammer price, by $p^* = (p_k^b + p_k^a)/2$, where k denotes the largest index, $p_k^a \le p_k^b$, p_k^b and p_k^a denote the kth bidding price and asking price, respectively. Finally, the winning buyer gets the resource and pays the corresponding seller p^*. The matching relationship between remaining buyers and sellers and corresponding hammer prices can be determined by repeating the above process.

3) Online Auction: An online auction [63] is an auction in which the auction process are carried out by buyers and sellers through the Internet platform, the sellers distribute the information of commodities or services to be sold on the platform, and the buyer participates in the competition by bidding, and finally sells them to the buyer with the highest (lowest) price. Compared with traditional auctions, its significant advantage is to break through the time and space constraints of traditional auctions. The participants can easily click the mouse to participate in the auction through the Internet.

4) Reverse Auction: A reverse auction [57] is a type of buyer-side auction in which the traditional relationship between buyers and sellers are reversed. Specifically, sellers compete to obtain business from the buyer and prices will ordinarily decrease since the sellers underbid each other. Thus, a reverse auction is a descending bid auction and is beneficial for buyers to save cost. We should note that the sellers are rational and they also want to benefit from the reverse auction, so the bid cannot be lower than the cost value of their commodities.

5) Hierarchical Auction: Hierarchical auction [59] is a kind of auction approach which utilizes hierarchical idea to solve a complicated allocation issue. The issue can be divide into multiple layers and each layer is coupled to each other. Each layer can be seen as a single resource allocation problem and we can use various auction approaches, e.g., combinatorial auction, double auction, reverse auction, etc. to address it.

In the next section, we will discuss how to adopt the combinatorial auction, double auction and other auction approaches for the resource allocation and pricing in the EC market.

IV. APPLICATION OF AUCTION APPROACHES IN EC

Considering the fact that different types of auction methods are suitable to address different types of problems in EC. In this section, we present a comprehensive view on the applications of auction-based approaches for EC under different types of auctions.

A. *Combinatorial Auction*

In the practical competitive market, the relationship between supplies and demands is always complicated. In recent years, considerable attentions have been focused on combinatorial auction to deal with combinatorial allocation problems. As shown in Table IV, we summarize the above-mentioned work in terms of the issue, objective, market structure (i.e., seller, buyer, auctioneer, commodity), scenarios and advantages.

TABLE IV
COMBINATORIAL AUCTION-BASED MECHANISM IN EC

Ref.	Issue	Objective	Market structure				Scenarios	Advantages
			Seller	Buyer	Auctioneer	Commodity		
[64]	Resource allocation and pricing	Efficient allocation	SPs	Infrastructure providers	Orchestrator	Processor, memory, storage	FC	An popular auction-based resource allocation platform
[65]	Resource allocation and pricing	Social welfare maximization	Edge/cloud servers	Mobile users	Edge/Cloud server	VM instances(CPU, memory, storage)	Cloud/Edge comput-ing	Guarantee IR and envy-free allocations, combining the advantages from position and combinatorial auctions, and greatly reduce the execution time
[66]	Resource allocation and pricing	Higher income and allocation efficiency	Fog nodes	IoT user	Fog server	Fog node services	FC	Guarantee TF, highly useful in various applications
[67]	Resource allocation and pricing	Near-optimal social welfare	Edge cloud nodes	Mobile users	A construted platform	Virtual Machine (VM) resources	ECC	Guarantee IR, CE and TF, and the communication latency is greatly shorten
[68]	Computation offloading	QoS, and efficient offloading	MEC service providers	User equipments	MEC service providers	Wireless and computational resources	MEC	System performance of the proposed algorithm outperform existing algorithms, consider demand heterogeneity of UEs
[69], [70]	Resource allocation and pricing	QoE, social welfare maximization	Base stations	Streamers	Edge system	Backhaul capacity and caching space	MEC	The proposed algorithm can be calculated in polynomial time, and greatly enhance overall system utility
[71]	Task offloading	Task execution time minimization	MBS/SBS	Vehicles	MBS/SBS	Wireless and computing resources	MEC	Effectively reduce system overhead, and the average time for completing a task is minimized
[72]	Resource allocation and price	QoS, and the profit of fog nodes maximization	Fog service providers	Mobile users	A trusted third party	Computation resource (CPU and memory resource)	FC	Guarantee IR, CE, and TF, and one seller servers multiple buyers simultaneously
[73], [74]	Resource management and pricing	Social welfare maximization	ESP	Mobile users	ESP	Computation resource	MBN	Guaranteeing the TF, IR and CE
[75]	Energy consumption and commu-nication costs	Energy consumption and communi-cation costs minimization	Applications	End-user devices/fog nodes	Applications	Microservices	FC	The placement strategy outperform others, the network topology is robust and generates less energy overhead than other topologies, and effectively protect privacy

In [64], the authors constructed an auction-based resource allocation platform wherein the resources as commodities mainly consist of processor, memory and storage. The platform includes three layers: SPs, SRs and manager. The highest layer consists of many SRs, i.e., buyers, which need a bundle of resources from the lowest layer, i.e., SPs (sellers). The auctioneer as the middle layer, which offers details of available resources and hosts the auction processes. Then, a resource allocation function based on combinatorial auction is applied to deal with the issue of the price competition between SPs and SRs. The method aims to obtain the optimal price among SRs and guarantees to provide fairly recompense for SPs. However, this work did not verify the effectiveness of the proposed method by any experiments. Moreover, the discussion for economic properties of the proposed mechanism was not given.

It is challenging to obtain optimal revenue or social welfare in MEC systems by effective allocation and pricing for limited edge/cloud resources. The authors in [65] solved the problem of the virtual machine (VM) instances allocation and pricing between MDs (buyers) and edge/cloud servers (sellers) by a combinatorial auction mechanism, called G-ERAP. The G-ERAP is integrated with the combinatorial auction and the greedy algorithm [76] to determine the winners and the payments. The novel G-ERAP combines the advantages from both position auction and combinatorial auction for satisfying heterogeneous requests of mobile users (MUs). The theoretical analysis demonstrated that G-ERAP can achieve IR while ensuring envy-free allocation. Experimental results showed that the revenue and social welfare obtained by G-ERAP are comparable to those obtained by CPLEX. However, as a two-level allocation mechanism, G-ERAP offloads tasks to edge servers or cloud servers without any consideration for different requirements and preferences of MUs. Furthermore, the G-ERAP mechanism cannot ensure the property of TF. It aims to achieve envy-free allocations by sacrificing TF.

To guarantee the TF, the authors in [66] proposed two types of truthful mechanisms, i.e., the fixed price based fog node allocation mechanism (FixP-FogNA) and the combinatorial auction based fog service allocation mechanism (CAuc-FogSA), both of which consider heterogeneous demands from end users. FixP-FogNA and CAuc-FogSA aim to effectively allocate limited fog services (i.e., computation, storage, and networking related services) of fog nodes (sellers) to various users (buyers) by adopting a fixed cost strategy and a combinatorial method, respectively. The winners and the payments are obtained by adopting truthful approximation algorithm. It is noteworthy that the “fixed price" stands for the fixed cost of corresponding fog node, namely a user should pay for using its service at a unit time slot in FixP-FogNA. The CAuc-FogSA is an incentive compatible mechanism which can guarantee economic property of TF. Compared with FixP-FogNA, CAuc-FogSA achieves higher revenue and allocation efficiency for fog service providers. On the contrary, FixP-FogNA has less computational complexity than CAuc-FogSA. However, the validity and effectiveness of the proposed mechanisms need to be demonstrated by experiments. Furthermore,

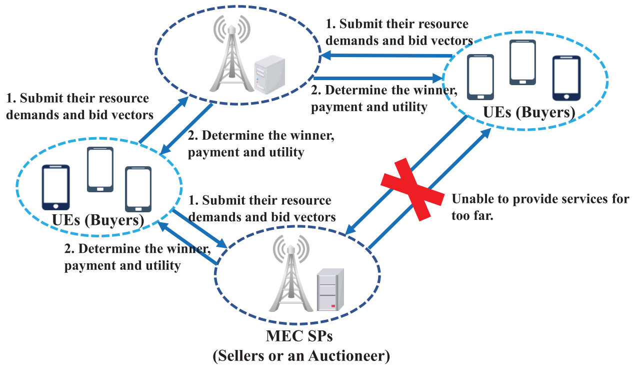


Fig. 4. The MEC network model.

the social welfare and other properties, e.g., IR and BB, can be considered in the future work.

In contrast to [65] and [66], authors in [67] addressed the similar problem, i.e., allocating limited VM resource allocation between the MUs as buyers and geo-distributed edge cloud nodes (ECNs) as sellers by a truthful auction-based VM resource allocation (AVA) mechanism. The AVA mechanism includes two main algorithms, i.e., the greedy winning bid selection algorithm and the payment determination algorithm, both of which can obtain near-optimal social welfare while ensuring TF, IR, and computational efficiency (CE). The winners and the payments are determined by the winning bid selection algorithm and payment determination algorithm in [67]. Moreover, the communication latency can be greatly shorten by the AVA mechanism based on the network paradigm of edge cloud computing (ECC) [77]. However, the other factors, e.g., bandwidth and quality of transmission, may need to be considered when evaluating the performance of the proposed mechanism.

In fact, a reasonable and efficient resource allocation mechanism not only guarantees the economic properties, e.g., IC, IR, and CE [65]–[67], but also ensures the QoE/QoS of UEs [33], [36], [78].

In [68], the authors jointly considered economic properties and UEs' QoS to construct an auction model based on matching relationship between multiple UEs and multiple MEC SPs in MEC networks. As shown in Fig. 4, UEs as buyers with heterogenous demands compete for limited wireless and computational resources from the MEC SPs, while MEC SPs play the roles of sellers and auctioneers. To solve the above resource allocation issue, a multi-round-sealed sequential combinatorial auction (MSSCA) mechanism is proposed, which consists of winners determination, bid strategy of users and the pricing process. The bid strategy of users is inspired by multi-round priority rule. Then, the winner determination process is transformed into a two-dimensional knapsack problem and can be solved by DP algorithms. The simulation results demonstrated that MSSCA can improve the system performance while maintaining well QoS for UEs. However, this work still has two shortages coming from the multi-round auction itself, i.e., the bidder drop problem and resource waste problem [68], which may restrict further improvement of the

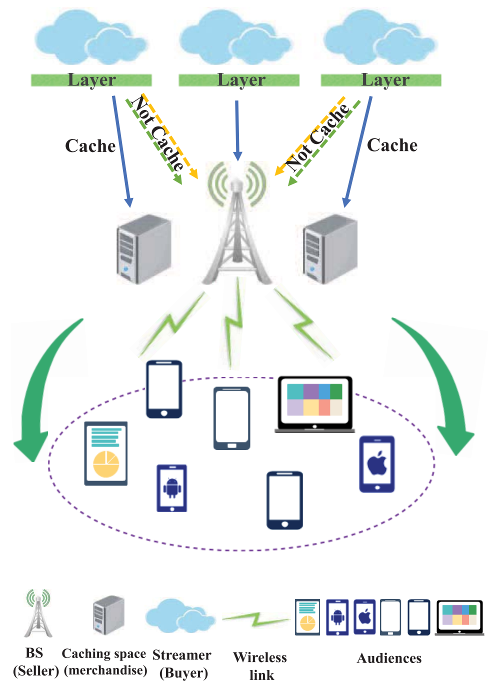


Fig. 5. System model of live video streaming services in MEC.

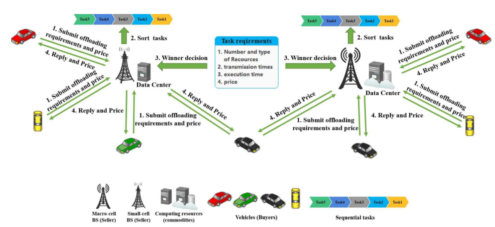


Fig. 6. The diagram of task offloading in MEC network.

system performance. Moreover, it is more practical to assume that the valuation function is nonlinear with the number of received resources [68], such as AR/VR [9] and live video streaming [69].

The authors in [69] tackled the limitations in [68]. They considered that the valuation function is given which is nonlinear with the number of received streamers. In order to improve the QoE of live video streaming services [79], [80] under limited backhaul capacity and caching space, they proposed an auction algorithm based on combinatorial clock auction (CCA) in streaming (CCAS) framework [69]. In such framework, BSs, streamers and caching space are treated as sellers, buyers and merchandise, respectively (as shown in Fig. 5). The edge system as an auctioneer hosts the auction process and determines the winners and caching space allocation. The CCAS includes two stages: the clock stage and the supplementary phase. In the first stage, sellers increase the prices and buyers submit their demands according to the prices in each round. In the second stage, the auctioneer determines the winners and their payments by VCG mechanism. Then, the problem of the caching space value evaluations and allocations was formulated as a variant of 0-1 knapsack problem [81], and was solved by DP algorithms in the CCAS. In order to further optimize the auction process and reduce the complexity of calculation, a method of identifying equivalent package sets is applied. The theoretical analysis demonstrates that CCAS can satisfy TF while achieving optimal efficiency. The overall system utility can be significantly improved by CCAS which is demonstrated by the simulation results. However, this work allocated the backhaul capacity by adopting a fixed rule when specifically determining the caching space allocation [70]. This may hinder its application and potentially constraint system efficiency.

As an extension of [69], the authors in [70] did more in-depth study for the same problem by improving the proposed algorithm of [69]. Two auction frameworks, i.e., edge combinatorial clock auction (ECCA) and combinatorial clock auction in stream (CCAS) are proposed. As shown in Fig. 5, to improve system efficiency and offer better QoS services for audiences, ECCA and CCAS focus on the issues of the backhaul capacity and caching space allocation (BCCSA), and the caching space value evaluations and allocations (CSVEA), respectively. In ECCA, the problem of BCCSA is formulated as an optimization problem dominated by the edge system, which specifically determines the allocation scheme of the backhaul capacity and caching space according to the requests of streamers, and is solved by a three dimension DP algorithm [70]. In CCAS, the problem of CSVEA is formulated as two optimization problems dominated by the streamers and the edge system respectively, and is solved by the DP algorithms. The simulations showed that ECCA outperforms the algorithms of CCAS, FSC, PC and FC [69] in terms of social welfare and average utility of each streamer. However, CCAS is a better method for achieving similar performance close to ECCA, but with lower computation complexity and higher scalability. In fact, CCAS can achieve higher scalability and lower computation complexity by sacrificing merely a little efficiency. To sum up, the property of TF and the optimality of efficiency are both guaranteed by ECCA and CCAS, as demonstrated theoretically. However, ECCA and CCAS did not take into account the latency requirements in the utility functions.

In order to improve task offloading efficiency in terms of tasks execution time, the authors in [71] described the task offloading problem as a multi-round sequential combination auction by considering mobile vehicles and macro-cell/small-cell base station (MBS/SBS) to be the buyers and sellers, respectively. The mobile devices have heterogeneous resource requirements and the MBS/SBS deploy various service nodes with limited wireless and computing resources. In the system, many vehicles submit diverse requirements and bid prices for nearby service nodes in sequence. After receiving the requests from the vehicles, the service node applies the winner decision algorithm to determine the winning vehicle and the payment. The optimal matching relationship between vehicles and service nodes can be transformed into a multi-dimensional grouping knapsack problem, and then is addressed by a DP algorithm. Compared to the existing task offloading algorithms [82]–[84], the proposed algorithm can obtain shortest average task competition time, effectively reduce system overhead, and is demonstrated by simulation results. However, the preferences of both vehicles and service nodes, can be considered to be an extension. Furthermore, the economic properties, e.g., TF and IR, should be guaranteed in the proposed mechanism.

Similar to [68]–[71], the authors in [72] took economic properties, users' QoS and resource allocation efficiency into account to design a combinatorial auction mechanism based on a dynamic resource allocation model. The model is composed of fog nodes, i.e., sellers, each of which owns heterogeneous computing resources and is deployed around MDs, i.e., buyers, which need to offload heterogeneous tasks to fog nodes, and a trustworthy third party, i.e., an auctioneer. The winner and the price are determined by the winner determination rule and the pricing rule, respectively. In addition, the pricing model has three billing methods: on-demand, daily and auction billing. The tasks are divided in terms of execution time, delay-sensitive and computational complexity. Moreover, unlike McAfee's mechanism [85] that one seller can only serve one buyer, the proposed mechanism allows one seller to serve multiple buyers simultaneously. Particularly, the resource overbooking and prediction algorithms based on LSTM-enabled [86] neural network and service level agreement violation (SLAV) feedbacks are proposed, which can dramatically eliminate the impact of low resource utilization even if during non-peak-hour. Thus, the mechanism achieves a high degree of QoS satisfaction for diverse tasks. The experiment results demonstrated that the proposed mechanism guarantees TF, IR, BB and EE. It is obvious that the proposed mechanism is superior to McAfee's mechanism. Moreover, similar to [66], the proposed mechanism can maximize the profit of SPs, i.e., fog nodes. However, the effectiveness of task scheduling was not considered in this work.

As an emerging decentralized technique, blockchain has been gaining considerable attentions. Recently, blockchain technique has been widely used in security and reliability field [34], [35]. Unfortunately, mining process cannot be supported by MDs with limited computing and storage capacities which hinders applications and developments of blockchain technique in EC.

In mobile blockchain networks (MBNs), the limited computing power and storage space of MDs (miners) lead to the mining issues. To address the issue, the authors in [73] transformed the mining task offloading problem as an auction by treating the edge computing service provider (ESP) plays the roles of the seller and the auctioneer, and MDs as buyers. As shown in Fig. 7, the ESP owns edge computing servers (ECSs) and deploys them around MDs. The MDs compete for computing services of nearby ECSs to process their mining tasks, and ESP decide the winners and the payments that MDs should pay ECSs. Then, an auction-based mechanism for resource allocation in MBNs was proposed to achieve social welfare maximization while satisfying the desirable economic properties, i.e., IR and TF. In addition, the mechanism contains an algorithm which is integrated with the greedy algorithm [76] and the VCG auction [87]–[89] that can obtain the winners and the payments while enhancing the trading frequency of participants in the system. The simulations demonstrated that the

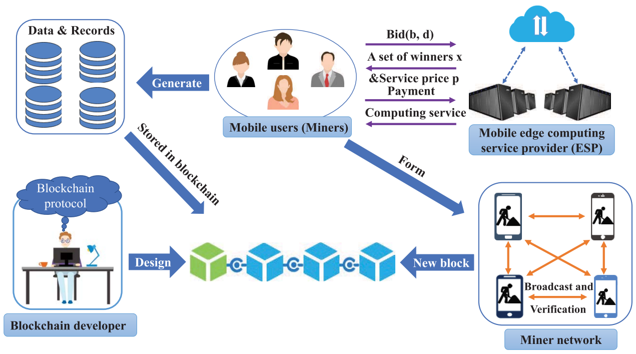


Fig. 7. Resource allocation for mobile blockchain in EC system.

proposed mechanism can obtain optimal allocation for computing resources. However, it is not practical to only consider MDs (miners) with constant demand. Moreover, the network effects function need to be verified by experiments.

Unlike [73] in which the buyers have constant demands, the authors in [74] considered the buyers with multi-demand in constructing auction-based mechanism. Similar to [73], a combinatorial auction-based allocation mechanism for computing resource was introduced, where the cloud/fog computing service provider (CFP) acts as the auctioneer and the seller, and MDs (miners) act as buyers. The MDs compete for nearby cloud/fog servers (CFSs) to process the mining tasks, where CFSs are deployed and managed by the CFP. The allocative externalities was considered in designing auction mechanism due to the competition among miners. Note that two bidding schemes: the constant-demand scheme and the multi-demand scheme, both of them can obtain social welfare maximization meanwhile ensuring desired economic properties (e.g., TF and IR) and CE. The main difference between the two bidding scheme is the restrictions on bidding. More concretely, each miner of the constant-demand scheme can only bid for resources in fixed quantity. In contrast, each miner of the multi-demand scheme can bid for resources in diverse quantity and submit their interesting demands and bids. The real-world experiments demonstrated that the proposed mechanisms can achieve optimal resource allocation, and offer valuable guidance for the application of blockchain technique in EC. However, enhancing total revenue of the server provider can be investigated in the future work.

Considering undesirable characteristics of MDs in EC, such as short-term power supply, which highlights the significance of energy overhead. To minimizes energy overhead and communication costs, the authors in [75] proposed a distributed fog service placement (DFSP) algorithm based on an iterative combinatorial auction. In each iterative of an auction, fog nodes (buyers) bid for a bundle of microservices (commodities) of the designated application (seller), where the designated application is determined by fog nodes before bidding. To determine which fog nodes obtain the bundle of microservices from the designated application and the price of the microservices, a dynamic pricing scheme is implemented. Unlike conventional auction model, their model is fully distributed, i.e., without a central auctioneer, and buyers decide whether or not to send their private data and to whom. This decentralized framework can avoid leakage of private information and trading details. The numerical examples showed that DFSP achieves minimum total cost of existing algorithms [90], [91]. Then, they evaluate the quality of the placement strategy of DFSP in terms of the CPU utilization, communication cost and the number of fog nodes, the results well verified its performance outperforms the other algorithms [90], [91]. Furthermore, the linear network topology of proposed system is more robust and generates less energy overhead than previous topologies, which was proofed by some experiments [90]. However, the proposed mechanism only allows an application trading with a fog node.

In summary, in this section, we have reviewed that combinatorial auctions are applied to addressing some issues of resource allocation, pricing scheme, task offloading and optimize energy consumption in EC. We can find that the effectiveness of those combinatorial auction-based mechanisms are theoretically and experimentally demonstrated. Although combinatorial auctions can achieve excellent allocation efficiency on a package of resources (or services) which belong to different types but complement each other, it is not suitable for resource allocation in independent tasks with single resource request. Moreover, in multi-user and multi-server scenarios, it is still a challenge to construct an effective auction mechanism to achieve efficient allocation over complex relationship between UEs with personalized requirements and SPs with heterogeneous resource distribution while satisfying the desired economic properties. Furthermore, some authors realize the essentiality and necessity of privacy preserving in EC [92], and the trend is continuing for a long time to come.

B. *Double Auction*

A double auction [56] is a popular method for its typical many-to-many structure and is widely applied in real-world markets [93]. Recently, the number of IoT MDs increases tremendously, and it has seen various applications and research of double auction-based algorithms in multi-user and multi-server scenarios of EC.

In [94], the authors addressed the issue of computing resource sharing via designing an incentive-compatible auction periodical mechanism (ICAM) between MDs as service users (buyers) and cloudlets as SPs (sellers). ICAM consists of three phases, i.e., winning candidate determination, assignment&pricing, and winner elimination. In the first phase, the auctioneer determines the winning candidates according to an ascending buyer set and a descending seller set. In the second phase, a pricing rule is adopted to ensure the TF for buyers. In the last phase, surplus winners are abandoned and one buyer can only match one seller. The winers and their payments are determined by Algorithms: ICAM-A&P and CAM-WE. The numerical results showed that ICAM can enhance resource utilization of cloudlets while guaranteeing TF, IR, and BB. Moreover, ICAM can attain around 50% of the system efficiency for the allocation scheme. However, ICAM only allows to match a seller in each auction. It is impractical and may not fully utilize the ability of resource-rich SPs, which could

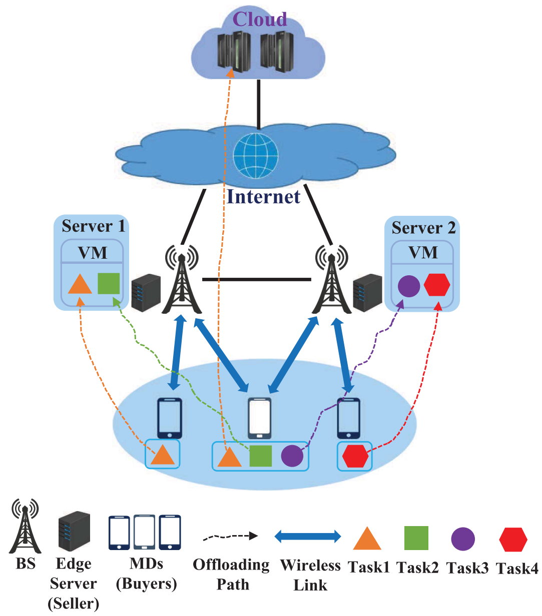


Fig. 8. A multi-task cross-server architecture in MEC.

have offered services for multiple users. Furthermore, they did not consider crucial influence of the locality characteristics of SPs on system efficiency.

Different from the matching manner in [94], some more reasonable and comprehensive mechanisms were proposed in the literature, i.e., [95]–[97]. In [95], the authors eliminated the shortcoming of the matching manner from [94], and jointly considered scarce computing resources and location properties. They introduced a single-round double auction mechanism based on breakeven (SDAB) in MEC. In the model, MDs (buyers) with individual awareness and preferences, compete for edge servers (sellers) with limited computation resources. As a trustworthy administrator, the auctioneer manages the whole auction process. The final winners and payments are determined by the SDAB algorithm. Compared with ICAM, SDAB allows one seller to support multiple buyers with offloading demands. Moreover, network economics and resource allocation were both considered in SDAB to maximize the number of resource tradings. The theoretical analysis and the numerical results verified that SDAB can guarantee IR and TF. It was shown that the number of successful trades obtained by SDAB is higher than those of ICAM by around 20% when the number of buyers increases to 50 under the unchanged number of sellers. However, SDAB cannot guarantee BB, and only considered the homogeneous tasks of MDs.

Considering BB and heterogeneity of both resources and tasks, the authors in [96] designed a cross-server resource allocation algorithm based on double auction (MADA) to enhance the system efficiency in MEC. As shown in Fig. 8, a kind of relation between MDs (buyers) and edge servers (sellers) is modeled as an auction, where MDs with heterogeneous tasks bid for diverse applications (commodities) from VMs of edge servers. In the model, the closest edge server as an auctioneer hosts the auction market. MADA is composed of three stages, i.e., remote cloud assistance, natural ordering and price & winner decision. In the first stage, the auctioneer decides whether to offload tasks to remote cloud according to the delay tolerance. In the second stage, they auction all types of applications (apps). In the last stage, the prices and winners are determined by price&winner algorithm. In particular, MADA can be calculated in polynomial time. The simulation results showed that MADA can effectively allocate resources while satisfying TF, IR and weakly BB. In addition, MADA can obtain higher system efficiency than the existing studies [94], [95]. Under the fixed number of edge servers, the overall utility of MADA is always higher than that of ICAM [94] via regulating number of buyers. The number of successful trading of ICAM is lower than MADA by around 50% when the number of buyers meets 50. However, the large growth of the number of both buyers and sellers will lead to higher computational complexity.

With rapid expansion of application for IIoT, the traditional resource allocation strategies are unable to satisfy the growing various requirements for edge devices. Thus, it is crucial to enhance resource utilization rate for an MEC-based IIoT scenario. Considering both network economics and locality constraints, the authors in [98] designed two double auction algorithms, i.e., a breakeven-based double auction (BDA) and a dynamic pricing based double auction (DPDA) to enhance the efficiency of resource utilization in MEC. The model is composed of a set of lightweight edge servers (sellers), a number of IIoT MDs (buyers) and an SP (auctioneer). BDA and DPDA both utilize dynamic pricing strategy to allocate resources and achieve the number of successful matching pairs maximization, while satisfying the economic properties of TF, IR, BB and EE. As shown in the simulation results, the utility of edge servers and IIoT MDs in DPDA were both higher than that in BDA under different number of IIoT MDs. Similar to ICAM [94], BDA maintains the TF between buyers and sellers by applying a breakeven, and DPDA achieves higher system efficiency by sacrificing TF. Moreover, the number of successful trades of DPDA is the highest compared to BDA and ICAM under different number of IIoT MDs. In summary, BDA and DPDA can substantially improve the system efficiency for MEC-based IIoT system. Although the performance of DPDA outperforms BDA and ICAM, DPDA cannot guarantee TF of sellers.

The above existing works [94]–[96], [98] improves the resource allocation efficiency mainly focus on the objective level, they ignore the subjectivity of participants in practical scenarios. To further improve resource utilization rate and achieve higher social welfare, the authors in [97] addressed the issue of computing resource allocation while considering the preferences of MDs. In the model, a set of MDs have heterogeneous computing requests act as buyers and sellers, the edge server with limited computing resources (commodities) play the roles of the seller and the auctioneer. Compared with the existing model [94]–[96], [98], the model of [97] can fully utilize computing resources of idle MDs. Thus, an auction scheme for computing resource allocation (ASCRA) mechanism in MEC system is proposed. The ASCRA is composed of three stages, namely, identification confirmation, candidate selection, and matching&pricing. In the first stage, ASCRA-IC algorithm identifies each device as a seller or a buyer based on their remaining resources. In the second stage, the resource condition and the delay condition are both considered in ASCRA-CS algorithm to select the candidate pairs among buyers and sellers. In the last stage, ASCRA-MP algorithm determines the winners and payments. The numerical results showed that ASCRA has higher number of successful trades than ICAM [94], BDA and DPDA [98] under different number of sellers, which due to idle MDs can share and sell their idle computing resources. The least number of successful trades is ICAM, which due to the usage of breakeven. Importantly, ASCRA meets all the desired economic properties. However, similar to DPDA, ASCRA aims to realize more higher system efficiency by sacrificing TF of sellers.

To achieve efficient resource allocation, the number of successful trades as a common objective is selected by [94]–[96], [98]. Different from those works, the authors in [99] enhanced the efficiency of computing resource trading in edge-assisted blockchain-based IoT. A trusted resource-coin loan system based on credit is established which consists of edge servers, i.e., lenders, which act as SPs own surplus resource coins, IoT devices, which play different roles include resource-coins lenders, borrowers and idle IoT devices, and a broker, i.e., the manager, which manages the trading market and provides trading-related services for participants. To meet the requirements of fast payment and frequent trading, a credit-based payment scheme is presented. Based on above, an iterative double-auction algorithm is executed by the broker to solve the optimization problems of resource-coin loan and loan pricing. Moreover, the broker performs the rule of loan pricing not only can extract the hidden information of participants, but also incentivize them to willing to trade. The theoretical analysis and simulations demonstrated that the proposed algorithm can achieve social welfare maximization while satisfying truthfulness, IR and BB. In addition, the algorithm can also protect privacy of trading participants.

Similar to the work in [99] that extracted hidden trading information to achieve optimal resource allocation by frequent iteration, the authors in [100] designed an optimal iterative double auction-based algorithm for computing resource trading in blockchain network which achieves social welfare maximization while preventing participants from privacy leakage. They constructed a pure P2P trading system for computing resources based on blockchain technique, which can ensure security and TF for each resource trade. The system is composed of the edge-CC service providers, i.e., sellers, which own redundant computing resources and sell them to IoT devices or nearby edge nodes, IoT devices, which play the roles of buyers, sellers and idle nodes, a broker, i.e., the controller, which adjusts and manages the trading market via a smart contract. The algorithm alternatively optimizes BAP, BMP and SMP optimization problems while satisfying the price rules to obtain optimal prices and winners by multiple iterations. Both the theoretical analysis and experimental results demonstrated that the proposed algorithm satisfies TF, IR, and BB. Unlike ICAM [94], SDAB [95] and BDA [98] utilize the breakeven approach to guarantee TF, the proposed algorithm adopts the effective price rules to achieve truthful trading while motivating both buyers and sellers participate in resource trading. However, this work tackled the issue of resource allocation supported by a centralized-control framework, which always meets a performance bottleneck when numerous deals occur.

Considering the emerging challenges of the performance bottleneck caused by the centralized framework [94]–[100], the authors in [101] proposed a secure and incentive-compatible double auction mechanism for computational resource sharing based on a decentralized EC framework, called DeCloud. DeCloud includes three major types of participants, i.e., clients, act as buyers which need computational resources, service providers, play the role of sellers which provide or share limited resources for buyers, and a distributed ledger, acts as a trusted execution environment which supports and executes auction algorithms based on smart contracts. In DeCloud, the impact of both potentially malicious providers and clients can be eliminated by distributed ledger backed by blockchain technique. Hence, DeCloud can prevent privacy leakage and information tampering of clients. To achieve high-quality and flexible matching, a heuristic matching mechanism is designed by utilizing an extensible bidding language with strong expressive power. Then, the optimal prices and the winners can be obtained by a DP algorithm in polynomial time. The economic properties of IC, IR and strongly BB were proved to be guaranteed by the theoretical analysis. In addition, the experiments were conducted on Google cluster-usage data showed that DeCloud can enhance optimal welfare from 70% to over 85% according to the exact market conditions. Nevertheless, this work cannot provide resource allocation services in the multi-task cross-server scenario.

In [102], the authors considered the issue of multi-task cross-server resource allocation while considering profit-driven nature of participants in blockchain-based MEC. A DPoS-based blockchain technique was adopted to achieve a decentralized and tamper-proof resource allocation consensus mechanism, which can protect users information from tampering by malicious edge servers. In the system, MDs, edge servers, and the computing and storage resources of edge servers are treated as buyers, sellers and commodities, respectively. Then, two double auction mechanisms are designed, i.e., a double auction mechanism based on breakeven (DAMB) and a breakeven-free double auction mechanism (BFDA), where BFDA is more efficient than DAMB, and both of them satisfy TF, IR and BB. Particularly, BFDA can address more tasks by sacrificing TF of buyers, which is similar as DPDA [98] and ASCRA [97]. Furthermore, the time complexity of both DAMB and BFDA is low. In order to ensure untampered and secure resource allocation, like DeCloud [101], the proposed algorithms are executed as smart contracts based on the DPoS-based mechanism in blockchain. The simulations showed that the performance of both DAMB and BFDA outperforms EDA and TIM [103] in terms of execution time and system efficiency. BFDA has better performance than DAMB in terms of average utilization rate of applications and average offloading rate of tasks. However, a more practical model with high mobility and time-varying of MDs for resource allocation can be investigated in the future work.

To jointly address the high-speed mobility and time-varying of moving vehicles in resource allocation, the authors in [104] proposed a dynamic allocation algorithm of edge resources (DAER) based on the double auction mechanism. In order to prevent third parties from tampering with users information, a resource transaction architecture backed by blockchain is constructed which acts as an auctioneer in an auction. In DAER, user vehicles act as buyers compete for resources from SPs, i.e., sellers, which own limited computing resources and capacities (commodities). The DAER algorithm is performed by a smart contract supported by a blockchain architecture, which jointly considers personalized demands of both vehicles and SPs. More importantly, the mobility of vehicles is considered in DAER, where the mobility leads to the location and the receiving service area of the moving vehicle are changing continuously. In order to provide resource freezing and pre-allocation service for moving vehicles, and maximize satisfaction between vehicles and SPs, three key algorithms, i.e., the state search algorithm, the selection of resource blocks and SPs algorithm, and resource freezing and pre-allocation algorithm, are designed. The first algorithm based on state prediction model can predict the next destination of the moving vehicle. The second algorithm can significantly decrease the service resources waste. The last algorithm can obtain an optimal freezing and pre-allocation strategy for the driving system to achieve the overall satisfaction value maximization of vehicle and SPs. In fact, the last algorithm is an improved genetic algorithm which determines the winner and the payment. The experiments showed that the performance of DAER outperforms some existing studies [105]–[108] in terms of task processing capabilities, resource utilization rate, and total satisfaction value. However, this work did not consider the issues of road congestion.

The aforementioned approaches only allow one task of an MD to be assigned to one SP, which potentially reduces resource utilization especially for those resource-rich SPs and against shorten the execution time of tasks. To overcome the challenge, the authors in [109] proposed a double auction-based mechanism for task offloading which supports one task of an MD can be serviced by multiple SPs. In the mechanism, MDs, edge servers and computational resources of edge servers are treated as buyers, sellers and commodities, respectively. Importantly, the novelty of the model is that one task of an MD can be split into multiple subtasks and distributed among multiple edge servers. In essence this means that all subtasks may be processed parallel over different edge servers. To efficiently offload heterogeneous tasks and obtain optimal social welfare, the winning bids determination problem is transformed into a cost flow minimization problem. Then, the cost-scaling push-relabel algorithm [110] is applied to solve the problem in polynomial time. The proposed mechanism satisfies IR, strong BB and CE. Compared to DPDA [98], the proposed mechanism can obtain higher social welfare and better scalability. However, unlike the previous mechanism, such as ICAM [94], SDAB [95] and BDA [98], this work cannot utilize the breakeven approach to achieve TF for both buyers and sellers.

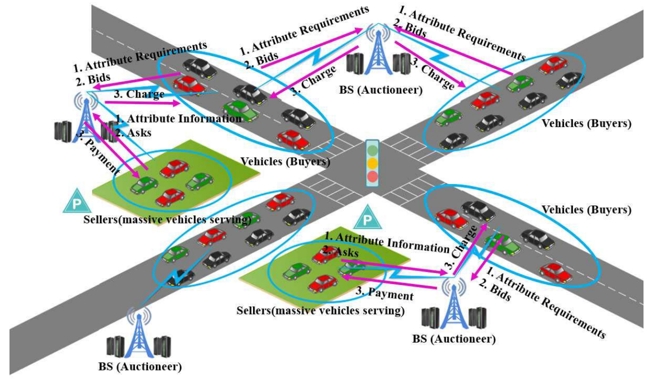


Fig. 9. System architecture of VFC.

In recently years, we have witnessed the widely applications of reinforcement learning (RL) in solving the problems of decision-making strategy [111]–[113]. It is enlightening to utilize the popular auction approaches that combined with RL to address the resource allocation problem.

In [114], the authors formulated the resource allocation problem as a double auction by seeing MEC servers, UEs/IoT devices, and a broker as the resource sellers, buyers and an auctioneer, respectively. In order to obtain the Nash equilibrium, the experience-weighted attraction (EWA) [115] algorithm is designed and running on all auction participants, where the EWA algorithm is integrated with RL and belief learning [116]. Moreover, the participants with limited resource can support EWA algorithm due to the low computational complexity of it. Thus, buyers and sellers can adapt to various changes and dynamically change their asking and bidding strategies based on the EWA algorithm in the auction market. The experiment results showed that the EWA algorithm can obtain an outstanding convergence performance while meeting profit demands of buyers and sellers, respectively. Specifically, the sellers will raise their asking prices with the increase of average cost but cannot raise extremely due to the constraints of the broker. On the contrary, the sellers will reduce their asking prices with the increase for the higher average capacity of their servers. This means that sellers can service more buyers and achieve higher profit. Moreover, the experiments showed that the buyers will not raise the bidding price a lot when increase their average value due to the number of buyers is large. However, the economic properties of the proposed mechanism need to be demonstrated theoretically and experimentally.

In order to allocate limited resources efficiently and reasonably, the above works design auction-based mechanism almost focus on the related attributes of price. However, the nature of EC system indicates that fully utilize price and various nonprice attributes is more effective in resource allocation meanwhile ensuring the network economics.

In [117], the authors jointly considered the price and nonprice attributes (e.g., location, reputation and computation capability) to design a multiattribute-based double auction (MADA) mechanism in vehicular fog computing (VFC). As shown in Fig. 9, auction-based VFC system consists of some

BSs and massive vehicles services, i.e., sellers, which provide various services for vehicles in the vicinity, and client vehicles, i.e., buyers, which need computing and storage resources (commodities) to process latency-sensitive tasks. The VFC system is divided into some subsystems based on the coverage of a BS. Then, the BS acts as an auctioneer to decide the winner and price. The MADA includes three main phases: matching, assignment and winner determination and pricing. In the first and second phase, the Kuhn-Munkres (KM) algorithm [118], [119] is applied to tackle the issue of maximizing weighted matching while maximizing resource utilization. In the last phase, MADA adopts a truthful and computationally efficient pricing algorithm [120] to determine the winner and the price. Theoretical analysis and experimental results demonstrated that the MADA can guarantee TF, IR, BB and CE. However, considering individual awareness and behavioral preferences of both buyers and sellers is a promising research direction to improve allocation efficiency.

Blockchain technique can achieve decentralized, tamper-proof and security resource allocation consensus mechanism, and has been widely applied to various field, such as financial transactions [123], IoT [46], healthcare [124], data storage [125], etc. However, limited communication and computing capabilities of MDs cannot meet the high requirements for blockchain mining process, which restricts the applications and developments of the blockchain technique in EC.

To overcome the above problem, the authors in [121] introduced a combinatorial double auction-based mechanism for the VM instances (commodities) trading, where MDs (buyers) act as miners compete with each other to migrate mining tasks to edge server providers (sellers). Each ESP owns different types of VM instances, varying in quality and price, and each MD need a package of different types of VM instances to process mining tasks. Two allocation algorithms, i.e., a step greedy algorithm (STGA) and a smooth greedy algorithm (SMGA) are proposed to determine the winners and allocate resources. In addition, a payment scheme algorithm (PSA) based on VCG auction is proposed to calculate trade prices, and a group buying rule is adopted to enhance the total utility of the system. The proposed mechanism can guarantee the economic properties of TF, IR and BB. The experimental results demonstrated that the performance of STGA outperforms SMGA, TACD [126], and CDARA [127] in terms of total utility, percentage of winning miners, and utilization of edge servers. However, the overall time complexity is increasing tremendously with the increase of the number of miners. Moreover, the available resources from nearby non-mining-devices need to be fully utilized.

Considering the available resource from idle devices in the vicinity, the authors in [122] dealt with the mining issues by a double auction mechanism based on a constructed collaborative mining network(CMN), where CMN is composed of numerous non-mining-devices and edge cloud. Similar to the model in [121], MDs (buyers) act as miners need to offload mining tasks to sharing-devices or edge cloud (seller). Therefore, the mechanism provides two kinds of offloading objects, i.e., non-mining sharing-devices and edge cloud. The task offloading problem is converted to a double auction game when miners offload mining tasks to neighboring non-mining-devices within the CMN. Then, the optimal auction price can be found by analyzing the Bayes-Nash Equilibrium [128]. When the offloading object is edge cloud, the interaction between edge cloud operator (ECO) and CMNs can be well modeled as a price-based optimization problem by stackelberg game. Then, the optimal price of ECO and the maximal profit of CMN can be obtained by NE analysis. The simulation results showed that the profits of CMNs under the proposed mechanism are higher than PECRM [129] by 6.86% on average. However, this work did not discuss some economic properties (e.g., IR and BB) and incentives for sharing-devices.

In this section, we review the existing literature of double auction-based resource allocation approaches in EC. We summarize those works along with references in Table V. As shown in the table, mostly works focus on resource allocation and pricing in various practical scenarios, such as MCC, MEC, IoT, IIoT, VFC, blockchain-based IoT, blockchain-based IIoV, etc. We can find that double auctions are more applicable for solving resource allocation problems in a type of EC market with "many-to-many" structure, where the resources should be better to be homogeneous. Moreover, the collusion and malicious bidding can be eliminated effectively. In the next section, we will discuss the use of multi-round or online auction approaches in EC.

C. *Online/Multi-Round Auction*

As an efficient and flexible form of e-commerce on the Internet, online auctions have been attracted widespread attention from both economic and engineering fields [130]–[134]. In recently years, the applications and developments of online auctions in EC have been accelerated by their timely responses and process for the demands of both sellers and buyers, and the fact that the explosive growth of online devices. Moreover, the multi-round auction also has been gained attention for allowing bidders to adopt different strategies in the whole process. However, how to fully utilize idle resources of MDs to assist in processing latency-sensitive and computing-intensive tasks on the edge of the network is still worth studying, which motivates many studies [63], [135]–[139].

In [135], the authors proposed an iterative auction algorithm for content placement based on a vehicular edge computing (VEC) system. The core objective of the system is to obtain caching contents in the least time. In the system, the contents are split into multiple content groups (CGs), which act as buyers bid for storage resources of idle vehicles located in multiple parking lots (sellers). The VEC system plays the role of the auctioneer to collect the bids from CGs and determine the winner. A reasonable utility function is introduced to evaluate the values of caching the contents of each CG to each of parking lots, and then each CG determines the bid and caching object according to the value. Based on above, the optimal placement relation between CGs and parking lots is converted to a transmission latency minimization problem which can be solved by the iterative ascending price auction-based caching algorithm. The algorithm can minimize the content access latency while improving the utilities of sellers. The numerical results

TABLE V
DOUBLE AUCTION-BASED MECHANISM IN EC

Ref.	Issue	Objective	Market structure				Scenarios	Advantages
			Seller	Buyer	Auctioneer	Commodity		
[94]	Resource allocation and pricing	Efficient allocation (the number of trade maximization)	Cloudlets	MDs	Edge server	Resources (memory and CPU capacity)	MCC	Guarantee IR, BB and TF (IC) for both the buyers and the sellers, and CE.
[95]	Resource allocation and pricing	The number of trade maximization	Edge servers	MDs	A trusted third party	Computing resources	MEC	Guarantee IR, BB and TF, improve the system efficiency, and consider the locality characteristics.
[96]	Resource allocation and pricing	The number of trade maximization	Edge servers	MDs	Closest edge server	Applications	MEC	Guarantee economic properties of IR, TF and weakly BB.
[98]	Resource allocation and pricing	The number of trade maximization	Edge servers	IIoT MDs	Service provider	Computing resources	MEC	Guarantee BB, IR, system efficient, and TF.
[97]	Resource allocation and pricing	The number of trade maximization	Edge servers and MDs	MDs	Edge server	Computing resources	MEC	Guarantee system efficiency, IR, BB and truthful properties, consider the preference of MDs and MDs can share their resources.
[99]	Resource allocation and pricing	Social welfare maximization	Edge servers	IoT devices	Broker	Computing resources	Edge IoT	Guarantee IR, TF and BB, protect privacy information, complete fast payment, frequent trading, and utilize blockchain technique.
[100]	Resource allocation and pricing	Social welfare maximization	Edge servers and IoT devices	IoT devices	Broker	Computing resources	Edge-cloud IoT	Guarantee IR, truthful, IC, system efficiency, BB and protecting privacies of participants.
[101]	Resource allocation and pricing	Social welfare maximization	SPs	Clients	A distributed ledger	Computing resources	EC	Guarantee strongly BB, and IR, a secure, decentralized and truthful auctioning mechanism.
[102]	Resource allocation and pricing	The system efficiency maximization	Edge servers	MDs	Trusted Edge servers	computing and storage resources	MEC	Guarantee BB, TF, and IR, and a trusted blockchain-based mechanism.
[104]	Resource allocation and pricing	The total satisfaction of users and SPs maximization	SPs	Vehicles	Blockchain-based system	Computing resources and capacities	EC	Maximize satisfaction between vehicles and SPs, improve resource utilization.
[109]	Task offloading	Social welfare optimization	Edge servers	MDs	MEC system	Workloads	MEC	Guarantee IR and strong BB, one task can be split into many subtasks, then assigned to different servers.
[114]	Resource allocation and pricing	The sum of utility maximization	MEC servers	UEs (IoT devices)	Broker	Computing resources	MEC	Combining the advantages of both RL and belief learning, outstanding convergence performance.
[117]	Resource allocation and pricing	Resource utilization maximization	Fog nodes	Client vehicles	The closest BS	Computing and storage resources	VFC	Guarantee CE, IR, BB, and TF, consider nonprice attributes (location, reputation, and computing power).
[121]	Resource allocation and pricing	The total utility of participants maximization	Edge server providers	MDs	Edge server	VM instances	MEC	Guarantee BB, IR and TF, higher total utility, good scalability and utilize blockchain technique.
[122]	Task offloading	Enhancing mining utility while maximizing profit	CMN and ECO	IoT MDs	Edge broker	Computing resources	Mobile blockchain network	Fully utilize available resource from idle devices in the vicinity and maximize the profit of CMN.

demonstrated validity and effectiveness of the proposed algorithm which achieve higher the performance of average latency by around 24% than the existing algorithms [140]. However, this work did not discuss the economic properties of the proposed algorithm. Moreover, how to incentivize parked vehicles to contribute their underutilized resources is a promising research direction toward enhancing resource utilization.

To fill the gap of [135], the authors in [63] utilized rewards to make resource owners are willing to share their resources. An online task offloading mechanism for EC IoT systems is designed to achieve long-term sum-of-rewards optimization based on Lyapunov optimization and VCG auction, without prior knowledge of the energy harvesting (EH), task arrivals or wireless channel statistics. The system consists of IoT devices, i.e., sellers, which generate computation tasks, broadcast them and the corresponding rewards, MDs, i.e., buyers, which bid for processing tasks to gain rewards, a task dispatcher, i.e., an auctioneer, which collects tasks and bids from IoT devices and MDs, respectively. In addition, the system supports highly dynamic EH process and the randomness of tasks arrival. The EH-powered MDs evaluate the value of task processing according to a Lyapunov optimization-based value function, and achieve long-term sum-of-rewards optimization by utilizing Lyapunov optimization technique. A winner and payment determination mechanism based on VCG auction is proposed to determine the winers and their payments. The optimality of tasks assignment strategy was demonstrated by theoretical analysis and simulations. Moreover, the proposed mechanism outperforms greedy auction and power consumption-aware auction in terms of sum-of-rewards. However, the proposed mechanism can only guarantee TF, the other economic properties, e.g., IR and BB, need to be guaranteed in the future work.

Similar to [63], the authors in [136] proposed two incentive auction-based mechanisms that both of them guarantee more economic properties. Two mechanisms include a VCG-based offline optimal auction mechanism (VCG-OFFOAM) which owns all future information, and an online truthful auction for social welfare maximization (ONTA-SWM) which based on the Myerson Theorem [141] and can obtain the optimal long-term social welfare without knowledge of future information. In the auction, the users and MDs are regarded as buyers and sellers respectively, the limited computation resources of the MDs are deemed as commodities, an MBS as an auctioneer administers the auction process. In VCG-OFFOAM, the VCG-based payment rule can find the optimal payment and maximizes the social welfare while satisfying TF and IR. In ONTA-SWM, the winners and corresponding payments are determined by an allocation rule based on primal-dual technique [142] and a payment rule. The payment rule introduces an auxiliary resource price function to support online dynamical pricing. Both the theoretical analysis and experimental results demonstrated that ONTA-SWM can achieve long-term social welfare maximization in polynomial time while satisfying TF and IR. In addition, the performance of ONTA-SWM closes to VCG-OFFOAM in terms of utility of users and the percentage of winners. However, this work did not discuss the BB of both VCG-OFFOAM and ONTA-SWM.

Similar to [63], [135] and [136] that aim to motivate resource providers (RPs) share their resources, the authors in [137] considered the issue of incentive profit maximization of RPs in both non-competitive and competitive scenarios based on market pricing model and auction model. The model consists of MDs, edge clouds (RPs), computation resources and a trusted third party, which are regarded as buyers, sellers, commodities, and an auctioneer, respectively. In the non-competitive scenarios, they jointly consider the utility of RPs and QoE of MDs, transform the incentive matching mechanism into a profit maximization problem based on market pricing model. Then, a pricing scheme is designed to deal with the optimization problem where the optimal price is found by a convex optimization method. Based on above, an online profit maximization multi-round auction (PMMRA) mechanism for resource trading between RPs and MDs in competitive scenarios is proposed, which achieves utility of RPs maximization while satisfying IC, IR and efficiency. In PMMRA, the winner and the final price are determined by utilizing price performance ratio (PPR) and payment rule based on Vickrey auction [16], respectively. The experiments showed that PMMRA can obtain higher total utility of RPs than the existing works [16], [68], [143]. However, a more practical model with mobility and randomness of MDs can be considered to be an extension.

Different from [137], the authors in [138] considered the mobility of vehicles in designed incentive auction mechanism. They jointly consider incentives and computing resource sharing for a smart VFC system by designing a multi-round multi-item parking reservation auction mechanism. The VFC system is integrated with parked vehicle assistance and smart parking [144]–[147]. The system consists of private parking operators, i.e., seller, which own multiple parking places and provide parking services, moving vehicles, i.e., buyers, which bid for parking reservation services and some of them provide computing services, fog node controller, i.e., an auctioneer, which manages the auction process, and parking slots are deemed as commodities. In the system, a single-round multi-item parking reservation auction (SMPRA) is introduced to guide the moving vehicles to desirable parking places and motivate the parked vehicles to share computing resources. To further improve the trading price, a multi-round multi-item parking reservation auction (MMPRA) on basic of SMPRA is proposed, which guarantees IC, IR and BB. In MMPRA, the profit of the FNC is increased by offload pricing update. In SMPRA and MMPRA, the allocation problem is formulated as a maximum weight perfect bipartite matching problem and is solved by KM algorithm [118], the payment rule improve the VCG mechanism based on Clarke pivot payments [141] to calculate payments. The simulation results demonstrated that the proposed algorithms improve the performance of the VFC system while achieving a win-win solution for the participants.

The above related works [63], [135]–[138] address resource allocation problem mostly focus on enhancing resource utilization of idle resource-rich devices. However, they do not consider the time constraint for latency-sensitive tasks.

In [139], the authors constructed a deadline-aware online resource auction (DORA) framework to dynamically allocate computational resources more efficiently in MEC system. In the DORA framework, MUs (buyers) bid for computational resources (commodities) to process a task queue, and the SP (seller/auctioneer) receives offloading demands from MUs, then determines the winners of MUs, the price that the winners should pay to the SP, and allocates computational resources to the winning MUs during each time slot.The task offloading problem is transformed as periodical auctions [148] that aims to achieve the social welfare maximization. It is noteworthy that the penalty is introduced to achieve tasks execution time constraint, i.e., complete tasks within the deadline. The DORA can obtain a close to offline-optimal long-term social welfare with polynomial time complexity by applied Lyapunov optimization techniques while satisfying the economic property of TF. The simulation results showed that DORA is near-superior to some existing algorithms (e.g., HCS, LQS, SAS) [139] in terms of social welfare, average task processing delay and average task dropping rate. The effectiveness of proposed DORA is clearly demonstrated by theoretical analysis and the simulation results. However, the economic properties, e.g., IR or BB, need to be guaranteed in DORA.

In summary, this section reviews the improvement of resource utilization for auction-based resource allocation and pricing in EC. We summarize those works along with references in Table VI. From the table, we can observe that the allocation schemes based on online (multi-round) auction have advantages in reducing latency. Also, well QoS and the economic properties, e.g., TF, IR, and BB can be guaranteed. However, online auctions may be impacted by network status, and multi-round auctions may cause high computing and communication consumption. In the next section, we will discuss the use of reverse auction approaches in EC.

D. *Reverse Auction*

Reverse auction [57] is a popular market-based mechanisms for resource allocation which aims to fairly allocate limited resources of SPs among multiple MDs which require a number of resources. Recently, some works [149]–[151] apply

TABLE VI
ONLINE/MULTI-ROUND AUCTION MECHANISM IN EC

Ref.	Issue	Objective	Market structure				Scenarios	Advantages
			Seller	Buyer	Auctioneer	Commodity		
[135]	Resource allocation and pricing	Average latency minimization	Parked vehicles	Content groups (CGs)	The VEC system	Storage resources	VEC	Guarantee well QoE, and minimize average latency.
[63]	Rewards-optimal computation offloading	Long-term sum-of-rewards optimization	IoT devices	MDs	Dispatcher	Computation resources	EC IoT	Guarantee the TF, MDs can achieve optimal utility, and support highly dynamic EH process and the randomness of tasks arrival.
[136]	Computation offloading	Long-term social welfare optimization	MDs	Users	MBS	Computational respurces	MEC	Guarantee TF and IR, well QoE, the proposed algorithm can be calculated in polynomial time.
[137]	Resource allocation and pricing	Profit maximization	Edge clouds	MDs	A trusted third party	Computation resources	MEC	Advantages: Guarantee IR, IC and efficiency.
[138]	Resource allocation and pricing	Total utility maximization	Parking place operators	On-the-move vehicles	FNC	Parking slots	VFC	Guarantee IC, IR, BB, well QoE, and achieve a win-win solution for the participants.
[139]	Resource allocation and pricing	Social welfare maximization	SPs	MUs	A trusted SP	Computational resource	MEC	The proposed algorithm can guarantee TF, and achieve close-to-offline-optimal social welfare.

the reverse auction-based mechanisms to resources allocation in EC.

In [149], the authors considered the problem of incentive task offloading between UEs and vehicles in MEC, where UEs have offloading tasks requests and vehicles with computing resources (commodities). The offloading relationship between UEs and vehicles can be well described by an auction model, where UEs, vehicles and a BS are treated as buyers, sellers and an auctioneer, respectively. To motivate vehicles to migrate computing tasks to the BS, a randomized auction-based incentive mechanism is proposed which can minimize the social cost while guaranteeing TF and IR. The winners and corresponding rewards are obtained by the randomized auction algorithm [149] which is integrated with the fractional VCG auction, the decomposition algorithm [152], [153] and greedy approximation algorithm. Then, the task assignment & resource allocation is transformed into a total network delay minimization problem, and then is solved by matching game [154], [155] and convex optimization methods, respectively. The numerical results showed that the social cost of the proposed mechanism less than renting scheme. The proposed mechanism effectively reduces the total network delay of the system. A promising research direction is to improve the allocation efficiency.

In order to enhance computing capability of MUs, similar to [149], the authors in [150] proposed a reverse auction mechanism combined with position auction [156] for resource allocation and pricing in MEC offloading systems. The system is composed of offloading users, i.e., buyers, which want to purchase computational resources (commodities) to process computing-intensive tasks, MEC servers, i.e., sellers, which own abundant computational resources and want to sell them, and a software-defined network (SDN) controller, i.e., an auctioneer, which administrate the auction process. A greedy bidding strategy based on restricted balanced bidding (RBB) algorithm [157] is introduced to calculate the bids of the MEC servers which aims to maximize their utilities. The winner determination problem (WDP) is transformed into a combinatorial optimization problem and can be tackled by an approximation algorithm in polynomial time. In addition, the pricing mechanism utilizes the generalized second price (GSP) auction to determine the allocation prices [156], [158]–[160]. Both the theoretical analysis and experimental results demonstrated that the proposed mechanism can guarantee IR, envy-free allocation [65], high resource utilization and well QoE of MUs. However, the fewer MUs may lead to lower efficiency of the system.

The approaches [149] and [150] do not consider the reliability and security of SPs, which may cause low allocation efficiency and even privacy leakage. Therefore, the authors in [151] designed a trustworthy caching and bandwidth allocation scheme based on reverse auction for MUs in the mobile social networks (MSNs). A trust evaluation model includes: direct evaluation and indirect evaluation, is constructed to help an MUs (buyer) to identify the reliability of nearby edge nodes (sellers) and find a better one to cache the contents. The direct evaluation is according to historical interactions and indirect evaluation is according to the suggestions from other MUs. Then, the optimal edge node for each MUs can be determined by the reverse auction algorithm. The Bayesian equilibrium is found by back induction method to determine the optimal caching space and bandwidth allocation for MUs. The proposed scheme can guarantee well QoE of MUs while preventing malicious edge nodes from attacking MUs. However, a more secure and reliable model that prevents participants from privacy leakage [100]–[102], [104] needs to be investigated in the future work.

In this section, we review the existing works of reverse auction-based resource allocation and pricing approaches in EC. As shown in Table VII, the proposed reverse auction-based mechanisms can do well in maximizing the utilities of MUs (buyers) while ensuring desirable economic properties. The satisfaction of buyers are also improved. In a reverse auction, the price as the decisive factor determines who the buyer chooses to buy from. However, the quality and credibility of sellers may not adopted as the evaluation criteria. Thus, it is crucial to integrate a comprehensive evaluation scheme into a reverse auction-based mechanism to achieve fair and

TABLE VII
REVERSE AUCTION MECHANISM IN EC

Ref.	Issue	Objective	Market structure				Scenarios	Advantages
			Seller	Buyer	Auctioneer	Commodity		
[149]	Task and resource allocation	Alleviate load and minimize total delay	Vehicles	UEs	BS	Computation resources	MEC	Guaranteeing TF and IR, minimize the social cost and network delay.
[150]	Resource allocation and pricing	The utility maximization	CSPs	Offloading users	SDN controller	Computational resources	MEC	Guarantee envy-free and IR, well Qos, and ensures users' satisfaction.
[151]	Caching and bandwidth allocation	The utility maximization	Edge nodes	MUs	The mobile user	Caching space and bandwidth resources	EC	Protect the network from the attacks of malicious edge nodes, and ensure well QoE.

feasible allocation. In the next section, we will discuss the use of hierarchical auction approaches in EC.

E. Hierarchical Auction

More recently, hierarchical strategies have been widely applied to study the distributed systems, e.g., MBNs [73], AI [161], 5G [162] and robotics [163]. The hierarchical auctions as an emerging approach can be applied to deal with the issues of resource allocation while achieving the social welfare maximization of the system.

To motivate the edge servers to provide services for MUs while ensuring security of the trading system, the authors in [58] proposed an incentive efficient three-stage auction mechanism (ETRA) for resource allocation in an MBN. The MUs (buyers) as miners have the same wireless network access point (auctioneer) defined as a group, and then compete with each other to offload mining tasks to edge servers (sellers) with computation resources (commodities). A group-buying scheme is designed to help miners to afford resources and incentivize edge servers to participate in resource trading. The ETRA consists of three stages, i.e., matching potential winner, matching cloudlet for AP and allocation the resource. In the first stage, the miners submit bids and resource requests to APs according to their preference for distance and QoS, then the potential winners and their payments can be calculated by the payment calculation algorithm based on VCG mechanism. In the second stage, APs find out the optimal matching between MUs and edge servers. In the last stage, the requested resources are placed in corresponding APs and are allocated to the miners. The theoretical analysis demonstrated that ETRA guarantee TF, IR and CE while achieving the social welfare maximization. The simulation results showed that the performance of the ETRA outperforms TACD [126] and HAF [164] in terms of utility of miners and social welfare. However, the computational complexity was not discuss in this work.

In this section, we discuss the problem of resource allocation by an incentive hierarchical auction-based mechanism in EC. The mechanism jointly considers the network economics and individual preferences of SPs to efficiently allocate resources for MUs. As aforementioned, hierarchical auctions are quite suitable for addressing resource allocation issues with obvious hierarchical structure, and they are coupling with each other. In the next section, we will discuss the use of revenue-optimal auction approaches in EC.

F. Revenue-Optimal Auction

It is still a challenge to fully utilize the resources of SPs to process computing-intensive tasks of MDs due to SPs have individual awareness and behavioral preferences. Recently, some works [59], [165]–[168] are motivated to address the problem via maximizing the revenue of SPs while aiming to satisfy the desirable economic properties, e.g., IC and IR.

In [165], the authors addressed the problem of function allocation based on a distributed auction-based mechanism in fog-based FaaS platforms. In the platform, the application developers act as buyers to bid for computing and storage resources (commodities), and the service nodes, which play the different roles include sellers and auctioneers contain three types: edge, intermediary and cloud, which offer computing and storage services for applications. In the auction, developers submit two types of bids, i.e., storage bids and processing bids, then service nodes reject or accept the requests according to their remaining resources. Particularly, the cloud nodes will accept all requests which are rejected by non-cloud nodes. In addition, they utilize the first-price auction to determine the final price. The simulation results demonstrated that the proposed mechanism can achieve revenue of service nodes maximization while stisfying all demands of application developers. Although the auction-based mechanism is simplistic, it opens a valuable research direction toward function placement in fog-based FaaS platforms. Moreover, a more practical model that jointly considers location of service nodes and available resources of clients can be investigated in the future work.

In contrast to [165], the authors in [166] placed more attention on incentives for resource trading in MEC, they achieved profit maximization of SPs by utilizing market-based pricing model. Similar as [137], this work also considered incentive algorithms of SPs both in non-competitive and competitive scenarios. In the non-competitive scenarios, the utility of SPs and the constraint on each user gain are jointly considered to establish a matching relationship between edge servers (sellers) and MDs (buyers) based on market-based pricing model. Then, apply it to design a profit maximization multi-round auction (PMMRA) algorithm in competitive scenarios which guarantees IC, IR and CE. The PMMRA algorithm can be calculated in polynomial time and consists of three crucial roles, i.e., bidding strategy, winner determination and payment determination. The first role evaluate which seller is better for buyers based on calculated the bid performance ratio (BPR). The second role determines the SP with higher price performance ratio (PPR) can be served by the SP.

TABLE VIII
REVENUE-OPTIMAL AUCTION MECHANISM IN EC

Ref.	Issue	Objective	Market structure				Scenarios	Advantages
			Seller	Buyer	Auctioneer	Commodity		
[165]	Resource allocation and pricing	Revenue maximization	Service nodes	Application developers	Service nodes	Computing and storage resources	FC	Opens a valuable research direction toward function placement in fog-based FaaS platforms.
[166]	Task offloading	Profit maximization	Edge servers	MDs	A trusted third party	Computational resources	MEC	PMMRA has polynomial-time complexity, and consider non-competitive/competitive scenarios.
[168]	Resource allocation and pricing	Profit maximization	SP	MUs	SP	Edge computing resource units	EC	Guarantee IC, IR, combine three hot technologies: EC, DL and blockchain, and well QoS.
[170]	Resource allocation and pricing	Profit maximization	ECSPs	MUs	ECSPs	VM instances	MEC	Facilitate the resource allocation for MEC networks, and well QoE.
[59]	Resource management and pricing	Profit maximization	Fog nodes	User devices	SP	Fog computing resource units	FC	Guarantee IC, IR, TF, combine three hot technologies: FC, DL and blockchain, and well QoS.

The final price can be calculated by Vickrey auction [16] that adopted by the last role. The simulation results showed that the performance of PMMRA outperforms the algorithms of [68] and [143] in terms of the utility of SPs and the number of offloaded tasks, respectively. However, a more effective incentive scheme which considers MDs have individual awareness and behavioral preferences can be considered to be an extension [169].

Different from [165], [166], the authors in [170] introduced a hierarchical MEC (HI-MEC) architecture which is inspired by the principles of LTE-advanced backhaul network and includes three levels, i.e., field, shallow, and deep cloudlets. To achieve profit maximization of the service provider, the supply-demand relation between edge-computing service provider (SP) and MUs can be formulated as an auction where MUs act as buyers, the VMs are deemed as commodities with diverse types which contain computing and communications resources, and the SP plays different roles include a seller and an auctioneer. Then, a two time scale optimization algorithms for resource allocation are proposed based on HI-MEC. Specifically, the auction-based profit maximization of the SP for VM pricing and VM assignment is transformed into a binary linear programming (BLP) [171] problem and then solved by the heuristic algorithms. Note that the prcie depends on the number of demands and the available resources. The bandwidth allocation problem is formulated as a convex optimization problem and then addressed by a centralized optimal solution. The simulation results demonstrated that the proposed algorithms can achieve the total network delay minimization. However, this work only supported a user request a single type VM at a time. A more efficient auction-based model [65] that allow a user requests a bundle of VMs of diverse types needs to be investigated in the future work.

In recent years, machine learning (ML) as a promising technology opens a new research direction toward addressing optimization problems on resource allocation of an auction market [59], [168].

To support blockchain applications in mobile environments, the authors in [168] utilized deep learning (DL) techniques to design the optimal auction for edge resources allocation to achieve blockchain-assisted EC. The model is composed of one SP, i.e., the seller and the auctioneer, which owns limited computing resources (commodities), multiple MUs, i.e., buyers, which play the role of miners and compete with each other for one computing resource unit by submitting bids. It is novel to create the neural networks to implement the allocation and payment rules based on an analytical solution of the optimal auction [172], and then calculating the winning probability of miners and their payments according to the inputs of neural networks, i.e., miners' bids. Therefore, the auction mechanism optimized by the neural networks, which is trained with valuations of the miners, to maximize the revenue of the SP while ensuring IC and IR. The experimental results verified that the proposed mechanism can obtain higher profit of the SP than the traditional sealed-bid auction [16]. However, this work only supported a single resource unit and did not consider the privacy protection of bidders.

As an extension of [168], the auction-based mechanism in [59] can support buyers to buy more than one resource unit in each auction, i.e., an optimal auction mechanism for resource allocation via leveraging deep learning in FC, which can achieve revenue maximization of SPs and ensure well QoS of users. The market consists of fog nodes, i.e., sellers, which owns a certain amount of computing resource units, miners, i.e., the buyers, that are lightweight devices bidding for computing resources to solve PoW puzzles, and one service provider, i.e., the auctioneer, that determines the resource assignments and the payments. The winners and payments are decided by the assignment and payment systems respectively, both of which are deep learning systems. The outputs of assignment and payment systems are assignment probabilities of miners and corresponding prices that winning miners need to pay, respectively. The simulation results demonstrated that the proposed mechanism is superior to the greedy algorithm [76] in terms of revenue, IC and IR violations. In addition, the TF is guaranteed by the mechanism. However, a worthy work of maximizing social welfare while satisfying IC, IR and TF needs to be investigated in the future work.

In summary, this section reviews the existing works which improve the allocation efficiency from the perspective of revenue optimization. These works along with their references are summarized in Table VIII. As shown in the table, the profit-driven nature of participants and well QoS of users are considered in designing incentive auction-based mechanisms to stimulate SPs to offer services for MDs. We observe that the decentralized and hierarchical auction architectures are considered for resource allocation in the works [165], [170]. In addition, some works study the combination of auction theory with DL to address resource allocation in blockchain networks [59], [168]. Generally, how to achieve revenue maximization while satisfying diverse requirements still needs to be investigated in the future work.

V. Open Issues and Future Research Directions

As we have discussed in aforementioned sections, auction theory can effectively solve various issues for EC, e.g., resource allocation, pricing scheme, task offloading, energy consumption optimization etc. In addition to the existing works, there are still several open challenges and promising research directions for EC are summarized as follows.

1) Security and Privacy: In EC market, we use auction approaches to fairly and efficiently allocate limited resources. However, the existence of colluding nodes and malicious nodes are inevitable to cause the issues of security and privacy due to their selfish and profit-driven nature. The malicious nodes may tamper trading information, and colluding nodes may leakage trading information and private data. Thus, how to eliminate the influence of the collusion and malicious nodes when design a auction-based mechanism is still a challenge in EC.

2) Auction Framework: For the traditional auction framework, a trusted third party always plays the role of the auctioneer to administrate each auction process [139]. However, in EC, an edge node as the auctioneer is inevitable to suffer from data leakage, information tampering and other privacy or security issues when the data are stored in malicious nodes [102]. We also observe that some works utilize blockchain technology to solve the issue [99]. However, the use of blockchain will cause huge resource consumption, which is clearly contrary to the fact that the edge network only owns limited resources. Therefore, it is imperative to design a new auction framework which does not rely on the trusted third party while guaranteeing auction efficiency.

3) Dynamic Environment: In traditional resource allocation problems, the resource owners and requesters, i.e., participants, are always in static state. On the contrary, the participants with high speed, e.g., vehicles and unmanned aerial vehicles, participate in a resource auction in EC. Although auction-based mechanisms in EC can offer the required computing and storage resources/services for the participants, it still faces great challenges with respect to high-speed mobility [104]. With the participants in high-speed movement state, how to design a dynamic auction-based allocation strategy which jointly consider the emergency factors, state prediction and privacy protection.

4) Heterogeneity: As mentioned above, the edge nodes as resource owners with heterogeneous resources, i.e., computing, storage and networking, participate in resource trading in the EC markets. The users and edge nodes as buyers and sellers, respectively, both of them have individual interests and preferences. Thus, they have different valuations of the resources. A properly valuation strategy can stimulate them to participate in the resource trading and improve allocation efficiency [135]. Therefore, a more reasonable valuation strategy for those heterogeneous resources in edge nodes should be investigated in the future worker.

5) Incentive Scheme: As a promising computing architecture, EC addresses the problem of the insufficient ability in processing computing intensive and latency-sensitive tasks of the MDs by utilizing idle resources of edge servers or UEs. However, SPs (edge servers or UEs) and SRs (MDs or users) are not always consistent in their interests due to their selfishness [13]. Many works [102], [149], [166], [173], [174] propose incentive auction-based mechanisms for EC in resource allocation [102], task offloading [149] and etc. However, the proposed mechanisms cannot fully utilize idle-resources of SPs due to individual awareness and behavioral preferences of both SPs and SRs. Thus, it is crucial to design incentive auction-based mechanisms according to the preferences and the conflicting interests of both sides of trading to stimulate them to participate in the resource trading. In addition, the existing works design incentive scheme mostly based on a single edge-server-based computing framework. It is worth investigating the incentive scheme based on edge-cloud computing framework for improving resource sharing [4].

6) Solutions of WDP: Almost all existing works solve the winner determination problem (WDP) generally by applying mathematical optimization techniques [69], [70]. However, it is difficult to attain the optimal solutions of the WDP because it belongs to NP-complete problems and is inapproximable [175]. Recently, ML plays an increasingly crucial role in addressing various NP-hard problems [176], [177]. Thus, auction theory combined with ML can be a prominent research direction to solve the WDP.

7) Combination of Auction Theory With Federated Learning: In order to enable IoT devices more smart, various intelligent applications are deployed to required IoT devices. However, most of the IoT devices cannot afford to computing resources for training those intelligent models. It also cannot guarantee the privacy and security for the data of end users. Fortunately, federated learning (FL) [178], [179] is a suitable solution to address the issues that mentioned above [45]. However, these work mostly assume that edge nodes are willing to participate in computing without any returns. In real world systems, edge nodes cannot offer resources unconditionally due to their limited resources, and have different preferences for different computing requests. Auction as an efficient method can be leveraged to design incentive mechanisms to motivate edge nodes contribute their resources [180]. For example, an incentive mechanism that integrates auction theory with FL is designed, which can greatly shorten the training times while enhancing the model accuracy [181]. These studies shows a promising research direction toward integrating auction approaches towards FL process [182].

In addition, the integration of auction theory and DL has also attracted attention recently [183]. In conclusion, the combination of auction theory and ML applying to EC will become an obvious research trend.

VI. Conclusion

In this survey, we have comprehensively introduced and discussed recent work of the applications of auction-based mechanisms for EC. Firstly, we have introduced the main paradigms of EC (i.e., cloudlets, FC, and MEC) and key advantages of each computing paradigm. Then, we have presented the related terminologies of auction theory and given a brief introduction of related auction methods. After that, we have presented detailed reviews, analyses and comparison of the approaches exploiting auction-based models to solve various resource allocation related issues in EC. Finally, several open challenges and promising research directions have indicated. In conclusion, we hope this paper can provide clear guidance for researchers who is interesting in applying auction approaches for EC.

References

[1] A. Galanopoulos, T. Salonidis, and G. Iosifidis, "Cooperative edge computing of data analytics for the Internet of Things," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 4, pp. 1166–1179, Dec. 2020.

[2] G. Dandachi, A. De Domenico, D. T. Hoang, and D. Niyato, "An artificial intelligence framework for slice deployment and orchestration in 5G networks," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 2, pp. 858–871, Jun. 2020.

[3] X. Wang, Y. Han, V. C. M. Leung, D. Niyato, X. Yan, and X. Chen, "Convergence of edge computing and deep learning: A comprehensive survey," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, pp. 869–904, 2nd Quart., 2020.

[4] Y. Zhang, X. Lan, J. Ren, and L. Cai, "Efficient computing resource sharing for mobile edge-cloud computing networks," *IEEE/ACM Trans. Netw.*, vol. 28, no. 3, pp. 1227–1240, Jun. 2020.

[5] Z. Ning *et al.*, "Deep reinforcement learning for intelligent Internet of Vehicles: An energy-efficient computational offloading scheme," *IEEE Trans. Cogn. Commun. Netw.*, vol. 5, no. 4, pp. 1060–1072, Dec. 2019.

[6] Y. Zuo, Y. Wu, G. Min, C. Huang, and K. Pei, "An intelligent anomaly detection scheme for micro-services architectures with temporal and spatial data analysis," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 2, pp. 548–561, Jun. 2020.

[7] Ç. Dilibal, "Development of edge-IoMT computing architecture for smart healthcare monitoring platform," in *Proc. 4th Int. Symp. Multidiscipl. Stud. Innov. Technol.*, Istanbul, Turkey, 2020, pp. 1–4.

[8] D. Zhang, F. R. Yu, and R. Yang, "Blockchain-based distributed software-defined vehicular networks: A dueling deep Q-learning approach," *IEEE Trans. Cogn. Commun. Netw.*, vol. 5, no. 4, pp. 1086–1100, Dec. 2019.

[9] B. Krogfoss, J. Duran, P. Perez, and J. Bouwen, "Quantifying the value of 5G and edge cloud on QoE for AR/VR," in *Proc. 10th Int. Conf. Qual. Multimedia Exp. (QoMEX)*, Athlone, Ireland, 2020, pp. 1–4.

[10] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," *IEEE Internet Things J.*, vol. 3, no. 5, pp. 637–646, Oct. 2016.

[11] F. Wang, M. Zhang, X. Wang, X. Ma, and J. Liu, "Deep learning for edge computing applications: A state-of-the-art survey," *IEEE Access*, vol. 8, pp. 58322–58336, 2020.

[12] "Edge Computing Market Size, Share & Trends Analysis Report By Component (Hardware, Software, Services, Edge-managed Platforms), By Application, By Industry Vertical, By Region, and Segment Forecasts, 2021–2028." May 2021. [Online]. Available: https://www.grandviewresearch.com/industry-analysis/edge-computing-market

[13] S. Pan and Y. Chen, "Energy-optimal scheduling of mobile cloud computing based on a modified Lyapunov optimization method," *IEEE Trans. Green Commun. Netw.*, vol. 3, no. 1, pp. 227–235, Mar. 2019.

[14] V. Krishna, *Auction Theory*. Amsterdam, The Netherlands: Academic, 2009.

[15] Y. Zhang, C. Lee, D. Niyato, and P. Wang, "Auction approaches for resource allocation in wireless systems: A survey," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1020–1041, 3rd Quart., 2013.

[16] W. Vickrey, "Counterspeculation, auctions, and competitive sealed tenders," *J. Financ.*, vol. 16, no. 1, pp. 8–37, 1961.

[17] Y. Luo, W. Ding, and B. Zhang, "Optimization of task scheduling and dynamic service strategy for multi-UAV-enabled mobile-edge computing system," *IEEE Trans. Cogn. Commun. Netw.*, vol. 7, no. 3, pp. 970–984, Sep. 2021, doi: 10.1109/TCCN.2021.3051947.

[18] C. Kai, H. Zhou, Y. Yi, and W. Huang, "Collaborative cloud-edge-end task offloading in mobile-edge computing networks with limited communication capability," *IEEE Trans. Cogn. Commun. Netw.*, vol. 7, no. 2, pp. 624–634, Jun. 2021.

[19] P. Porambage, J. Okwuibe, M. Liyanage, M. Ylianttila, and T. Taleb, "Survey on multi-access edge computing for Internet of Things realization," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 4, pp. 2961–2991, 4th Quart., 2018.

[20] R. Yang, F. R. Yu, P. Si, Z. Yang, and Y. Zhang, "Integrated blockchain and edge computing systems: A survey, some research issues and challenges," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 2, pp. 1508–1532, 2nd Quart., 2019.

[21] W. Yu *et al.*, "A survey on the edge computing for the Internet of Things," *IEEE Access*, vol. 6, pp. 6900–6919, 2017.

[22] U. Habiba and E. Hossain, "Auction mechanisms for virtualization in 5G cellular networks: Basics, trends, and open challenges," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 3, pp. 2264–2293, 3rd Quart., 2018.

[23] M. Satyanarayanan, P. Bahl, R. Caceres, and N. Davies, "The case for VM-based cloudlets in mobile computing," *IEEE Pervasive Comput.*, vol. 8, no. 4, pp. 14–23, Oct.–Dec. 2009.

[24] H. T. Dinh, C. Lee, D. Niyato, and P. Wang, "A survey of mobile cloud computing: Architecture, applications, and approaches," *Wireless Commun. Mobile Comput.*, vol. 13, no. 18, pp. 1587–1611, 2013.

[25] F. Bonomi, R. Milito, J. Zhu, and S. Addepalli, "Fog computing and its role in the Internet of Things," in *Proc. 1st Ed. MCC Workshop Mobile Cloud Comput.*, Helsinki, Finland, 2012, pp. 13–16.

[26] L. M. Vaquero and L. Rodero-Merino, "Finding your way in the fog: Towards a comprehensive definition of fog computing," *ACM SIGCOMM Comput. Commun. Rev.*, vol. 44, no. 5, pp. 27–32, 2014.

[27] C. Yi, J. Cai, K. Zhu, and R. Wang, "A queueing game based management framework for fog computing with strategic computing speed control," *IEEE Trans. Mobile Comput.*, early access, Sep. 23, 2020, doi: 10.1109/TMC.2020.3026194.

[28] C. Mouradian, D. Naboulsi, S. Yangui, R. H. Glitho, M. J. Morrow, and P. A. Polakos, "A comprehensive survey on fog computing: State-of-the-art and research challenges," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 1, pp. 416–464, 1st Quart., 2018.

[29] W. Y. B. Lim *et al.*, "Decentralized edge intelligence: A dynamic resource allocation framework for hierarchical federated learning," *IEEE Trans. Parallel Distrib. Syst.*, vol. 33, no. 3, pp. 536–550, Mar. 2022.

[30] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young, "Mobile edge computing—A key technology towards 5G," ETSI, Sophia Antipolis, France, Rep., vol. 11, no. 11, 2015, pp. 1–16.

[31] K. Peng *et al.*, "Joint optimization of service chain caching and task offloading in mobile edge computing," *Appl. Soft Comput.*, vol. 103, May 2021, Art. no. 107142.

[32] C. Yi, J. Cai, R. Wang, and K. Zhu, "Computation offloading game for edge computing with strategic local pre-processing time-length," in *Proc. IEEE 92nd Veh. Technol. Conf. (VTC-Fall)*, Victoria, BC, Canada, 2020, pp. 1–5.

[33] Z. Ullah, F. Al-Turjman, and L. Mostarda, "Cognition in UAV-aided 5G and beyond communications: A survey," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 3, pp. 872–891, Sep. 2020.

[34] T. Salman, M. Zolanvari, A. Erbad, R. Jain, and M. Samaka, "Security services using blockchains: A state of the art survey," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 1, pp. 858–880, 1st Quart., 2019.

[35] A. Asheralieva and D. Niyato, "Bayesian reinforcement learning and Bayesian deep learning for blockchains with mobile edge computing," *IEEE Trans. Cogn. Commun. Netw.*, vol. 7, no. 1, pp. 319–335, Mar. 2021.

[36] R. Han, Y. Wen, L. Bai, J. Liu, and J. Choi, "Rate splitting on mobile edge computing for UAV-aided IoT systems," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 4, pp. 1193–1203, Dec. 2020.

[37] R. Roman, J. Lopez, and M. Mambo, "Mobile edge computing, fog *et al.*: A survey and analysis of security threats and challenges," *Future Gener. Comput. Syst.*, vol. 78, pp. 680–698, Jan. 2018.

[38] K. Dolui and S. K. Datta, "Comparison of edge computing implementations: Fog computing, cloudlet and mobile edge computing," in *Proc. Global Internet Things Summit (GIoTS)*, Geneva, Switzerland, 2017, pp. 1–6.

[39] J. Ren, D. Zhang, S. He, Y. Zhang, and T. Li, "A survey on end-edge-cloud orchestrated network computing paradigms: Transparent computing, mobile edge computing, fog computing, and cloudlet," *ACM Comput. Surv.*, vol. 52, no. 6, pp. 1–36, 2019.

[40] C. Yi, S. Huang, and J. Cai, "Joint resource allocation for device-to-device communication assisted fog computing," *IEEE Trans. Mobile Comput.*, vol. 20, no. 3, pp. 1076–1091, Mar. 2021.

[41] H. Guo, J. Liu, and J. Lv, "Toward intelligent task offloading at the edge," *IEEE Netw.*, vol. 34, no. 2, pp. 128–134, Mar./Apr. 2020.

[42] J. Xu, S. Wang, A. Zhou, and F. Yang, "Edgence: A blockchain-enabled edge-computing platform for intelligent IoT-based dApps," *China Commun.*, vol. 17, no. 4, pp. 78–87, Apr. 2020.

[43] H. Guo and J. Liu, "UAV-enhanced intelligent offloading for Internet of Things at the edge," *IEEE Trans. Ind. Informat.*, vol. 16, no. 4, pp. 2737–2746, Apr. 2020.

[44] L. Yang, H. Yao, J. Wang, C. Jiang, A. Benslimane, and Y. Liu, "Multi-UAV-enabled load-balance mobile-edge computing for IoT networks," *IEEE Internet Things J.*, vol. 7, no. 8, pp. 6898–6908, Aug. 2020.

[45] X. Wang, C. Wang, X. Li, V. C. M. Leung, and T. Taleb, "Federated deep reinforcement learning for Internet of Things with decentralized cooperative edge caching," *IEEE Internet Things J.*, vol. 7, no. 10, pp. 9441–9455, Oct. 2020.

[46] C. K. Pyoung and S. J. Baek, "Blockchain of finite-lifetime blocks with applications to edge-based IoT," *IEEE Internet Things J.*, vol. 7, no. 3, pp. 2102–2116, Mar. 2020.

[47] F. Liang, W. Yu, X. Liu, D. Griffith, and N. Golmie, "Toward edge-based deep learning in industrial Internet of Things," *IEEE Internet Things J.*, vol. 7, no. 5, pp. 4329–4341, May 2020.

[48] W. Dou, X. Zhao, X. Yin, H. Wang, Y. Luo, and L. Qi, "Edge computing-enabled deep learning for real-time video optimization in IIoT," *IEEE Trans. Ind. Informat.*, vol. 17, no. 4, pp. 2842–2851, Apr. 2021.

[49] X. Xu, Q. Wu, L. Qi, W. Dou, S.-B. Tsai, and M. Z. A. Bhuiyan, "Trust-aware service offloading for video surveillance in edge computing enabled Internet of Vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 3, pp. 1787–1796, Mar. 2021.

[50] J. Liu, H. Guo, J. Xiong, N. Kato, J. Zhang, and Y. Zhang, "Smart and resilient EV charging in SDN-enhanced vehicular edge computing networks," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 1, pp. 217–228, Jan. 2020.

[51] H. Liu, P. Zhang, G. Pu, T. Yang, S. Maharjan, and Y. Zhang, "Blockchain empowered cooperative authentication with data traceability in vehicular edge computing," *IEEE Trans. Veh. Technol.*, vol. 69, no. 4, pp. 4221–4232, Apr. 2020.

[52] Z. Xiong, J. Kang, D. Niyato, P. Wang, and H. V. Poor, "Cloud/edge computing service management in blockchain networks: Multi-leader multi-follower game-based ADMM for pricing," *IEEE Trans. Services Comput.*, vol. 13, no. 2, pp. 356–367, Mar./Apr. 2020.

[53] Z. Xiong, S. Feng, W. Wang, D. Niyato, P. Wang, and Z. Han, "Cloud/fog computing resource management and pricing for blockchain networks," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4585–4600, Jun. 2019.

[54] Z. Xiong, Y. Zhang, D. Niyato, P. Wang, and Z. Han, "When mobile blockchain meets edge computing," *IEEE Commun. Mag.*, vol. 56, no. 8, pp. 33–39, Aug. 2018.

[55] T. H. T. Le *et al.*, "Auction mechanism for dynamic bandwidth allocation in multi-tenant edge computing," *IEEE Trans. Veh. Technol.*, vol. 69, no. 12, pp. 15162–15176, Dec. 2020.

[56] J. Shyuan, W. Lim, Z. Xiong, T. D. Niyato, C. Leung, and C. Miao, "A double auction mechanism for resource allocation in coded vehicular edge computing," *IEEE Trans. Veh. Technol.*, early access, Nov. 30, 2021, doi: 10.1109/TVT.2021.3131395.

[57] S. Parsons, J. A. Rodriguez-Aguilar, and M. Klein, "Auctions and bidding: A guide for computer scientists," *ACM Comput. Surveys*, vol. 43, no. 2, pp. 1–59, 2011.

[58] C. Xia, H. Chen, X. Liu, J. Wu, and L. Chen, "ETRA: Efficient three-stage resource allocation auction for mobile blockchain in edge computing," in *Proc. IEEE 24th ICPADS*, Singapore, 2018, pp. 701–705.

[59] N. C. Luong, Y. Jiao, P. Wang, D. Niyato, D. I. Kim, and Z. Han, "A machine-learning-based auction for resource trading in fog computing," *IEEE Commun. Mag.*, vol. 58, no. 3, pp. 82–88, Mar. 2020.

[60] S. De Vries and R. V. Vohra, "Combinatorial auctions: A survey," *INFORMS J. Comput.*, vol. 15, no. 3, pp. 284–309, 2003.

[61] M. Prates, P. H. Avelar, H. Lemos, L. C. Lamb, and M. Y. Vardi, "Learning to solve NP-complete problems: A graph neural network for decision TSP," in *Proc. AAAI Conf. Artif. Intell.*, vol. 33, 2019, pp. 4731–4738.

[62] D. Friedman, *The Double Auction Market: Institutions, Theories, and Evidence*. London, U.K.: Routledge, 2018.

[63] D. Zhang *et al.*, "Near-optimal and truthful online auction for computation offloading in green edge-computing systems," *IEEE Trans. Mobile Comput.*, vol. 19, no. 4, pp. 880–893, Apr. 2020.

[64] L. Fawcett, M. Broadbent, and N. Race, "Combinatorial auction-based resource allocation in the fog," in *Proc. 5th EWSDN*, Den Haag, The Netherlands, 2016, pp. 62–67.

[65] T. Bahreini, H. Badri, and D. Grosu, "An Envy-free auction mechanism for resource allocation in edge computing systems," in *Proc. IEEE/ACM SEC*, Seattle, WA, USA, 2018, pp. 313–322.

[66] A. Bandyopadhyay, T. S. Roy, V. Sarkar, and S. Mallik, "Combinatorial auction-based fog service allocation mechanism for IoT applications," in *Proc. 10th Int. Conf. Cloud Comput. Data Sci. Eng.*, Noida, India, 2020, pp. 518–524.

[67] G. Gao, M. Xiao, J. Wu, H. Huang, S. Wang, and G. Chen, "Auction-based VM allocation for deadline-sensitive tasks in distributed edge cloud," *IEEE Trans. Services Comput.*, vol. 14, no. 6, pp. 1702–1716, Nov./Dec. 2021.

[68] H. Zhang, F. Guo, H. Ji, and C. Zhu, "Combinational auction-based service provider selection in mobile edge computing networks," *IEEE Access*, vol. 5, pp. 13455–13464, 2017.

[69] Y.-H. Hung, C.-Y. Wang, and R.-H. Hwang, "Combinatorial clock auction for live video streaming in mobile edge computing," in *Proc. IEEE INFOCOM WKSHPS*, Honolulu, HI, USA, 2018, pp. 196–201.

[70] Y.-H. Hung, C.-Y. Wang, and R.-H. Hwang, "Optimizing social welfare of live video streaming services in mobile edge computing," *IEEE Trans. Mobile Comput.*, vol. 19, no. 4, pp. 922–934, Apr. 2020.

[71] S. Yang, "A task offloading solution for Internet of Vehicles using combination auction matching model based on mobile edge computing," *IEEE Access*, vol. 8, pp. 53261–53273, 2020.

[72] F. Zhang, Z. Tang, M. Chen, X. Zhou, and W. Jia, "A dynamic resource overbooking mechanism in fog computing," in *Proc. IEEE 15th Int. Conf. Mobile Ad Hoc Sens. Syst. (MASS)*, Chengdu, China, 2018, pp. 89–97.

[73] Y. Jiao, P. Wang, D. Niyato, and Z. Xiong, "Social welfare maximization auction in edge computing resource allocation for mobile blockchain," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Kansas City, MO, USA, 2018, pp. 1–6.

[74] Y. Jiao, P. Wang, D. Niyato, and K. Suankaewmanee, "Auction mechanisms in cloud/fog computing resource allocation for public blockchain networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 30, no. 9, pp. 1975–1989, Sep. 2019.

[75] P. Kayal and J. Liebeherr, "Distributed service placement in fog computing: An iterative combinatorial auction approach," in *Proc. IEEE 39th ICDCS*, Dallas, TX, USA, 2019, pp. 2145–2156.

[76] Y. Akçay, H. Li, and S. H. Xu, "Greedy algorithm for the general multidimensional knapsack problem," *Ann. Oper. Res.*, vol. 150, no. 1, pp. 17–29, 2007.

[77] U. Drolia *et al.*, "The case for mobile edge-clouds," in *Proc. IEEE 10th Int. Conf. Ubiquitous Intell. Comput. Auton. Trust. Comput. (UIC/ATC)*, 2013, pp. 209–215.

[78] Y. Yin, Z. Cao, Y. Xu, H. Gao, R. Li, and Z. Mai, "QoS prediction for service recommendation with features learning in mobile edge computing environment," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 4, pp. 1136–1145, Dec. 2020.

[79] H. Schwarz, D. Marpe, and T. Wiegand, "Overview of the scalable video coding extension of the H.264/AVC standard," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 17, no. 9, pp. 1103–1120, Sep. 2007.

[80] C. Zhan and G. Yao, "SVC video delivery in cache-enabled wireless HetNet," *IEEE Syst. J.*, vol. 12, no. 4, pp. 3885–3888, Dec. 2018.

[81] G. Dantzig, *Discrete-Variable Extremum Problems*. Princeton, NJ, USA: Princeton Univ. Press, 2016.

[82] M.-H. Chen, B. Liang, and M. Dong, "Joint offloading decision and resource allocation for multi-user multi-task mobile cloud," in *Proc. IEEE ICC*, Kuala Lumpur, Malaysia, 2016, pp. 1–6.

[83] T. Zhao, S. Zhou, X. Guo, and Z. Niu, "Tasks scheduling and resource allocation in heterogeneous cloud for delay-bounded mobile edge computing," in *Proc. IEEE ICC*, Paris, France, 2017, pp. 1–7.

[84] T. Z. Oo, N. H. Tran, W. Saad, D. Niyato, Z. Han, and C. S. Hong, "Offloading in HetNet: A coordination of interference mitigation, user association, and resource allocation," *IEEE Trans. Mobile Comput.*, vol. 16, no. 8, pp. 2276–2291, Aug. 2017.

[85] R. P. McAfee, "Mechanism design by competing sellers," *Econometrica*, vol. 61, no. 6, pp. 1281–1312, 1993.

[86] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.

[87] E. H. Clarke, "Multipart pricing of public goods," *Public Choice*, vol. 11, no. 1, pp. 17–33, 1971.

[88] T. Groves, "Incentives in teams," *Econometrica*, vol. 41, no. 1, pp. 617–631, 1973.

[89] L. M. Ausubel and P. Milgrom, "The lovely but lonely Vickrey auction," in *Combinatorial Auctions*, vol. 17. Cambridge, MA, USA: MIT Press, 2006, pp. 22–26.

[90] C. Pham, N. H. Tran, S. Ren, W. Saad, and C. S. Hong, "Traffic-aware and energy-efficient vNF placement for service chaining: Joint sampling and matching approach," *IEEE Trans. Services Comput.*, vol. 13, no. 1, pp. 172–185, Jan./Feb. 2020.

[91] A. Beloglazov and R. Buyya, "Optimal online deterministic algorithms and adaptive heuristics for energy and performance efficient dynamic consolidation of virtual machines in cloud data centers," *Concurr. Comput. Pract. Exp.*, vol. 24, no. 13, pp. 1397–1420, 2012.

[92] X. Wang, M. Umehira, B. Han, H. Zhou, P. Li, and C. Wu, "An efficient privacy preserving spectrum sharing framework for Internet of Things," *IEEE Access*, vol. 8, pp. 34675–34685, 2020.

[93] X. Zhai, T. Zhou, C. Zhu, B. Chen, W. Fang, and K. Zhu, "Truthful double auction for joint Internet of Energy and profit optimization in cognitive radio networks," *IEEE Access*, vol. 6, pp. 23180–23190, 2018.

[94] A.-L. Jin, W. Song, and W. Zhuang, "Auction-based resource allocation for sharing cloudlets in mobile cloud computing," *IEEE Trans. Emerg. Topics Comput.*, vol. 6, no. 1, pp. 45–57, Jan.–Mar. 2018.

[95] Y. Yue, W. Sun, and J. Liu, "A double auction-based approach for multi-user resource allocation in mobile edge computing," in *Proc. 14th Int. Wireless Commun. Mobile Comput. Conf.*, Limassol, Cyprus, 2018, pp. 805–810.

[96] Y. Yue, W. Sun, and J. Liu, "Multi-task cross-server double auction for resource allocation in mobile edge computing," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Shanghai, China, 2019, pp. 1–6.

[97] R. Zhang, W. Shi, J. Zhang, and W. Liu, "An auction scheme for computing resource allocation in D2D-assisted mobile edge computing," in *Proc. IEEE GLOBECOM*, Waikoloa, HI, USA, 2019, pp. 1–6.

[98] W. Sun, J. Liu, Y. Yue, and H. Zhang, "Double auction-based resource allocation for mobile edge computing in industrial Internet of Things," *IEEE Trans. Ind. Informat.*, vol. 14, no. 10, pp. 4692–4701, Oct. 2018.

[99] Z. Li, Z. Yang, S. Xie, W. Chen, and K. Liu, "Credit-based payments for fast computing resource trading in edge-assisted Internet of Things," *IEEE Internet Things J.*, vol. 6, no. 4, pp. 6606–6617, Aug. 2019.

[100] Z. Li, Z. Yang, and S. Xie, "Computing resource trading for edge-cloud-assisted Internet of Things," *IEEE Trans. Ind. Informat.*, vol. 15, no. 6, pp. 3661–3669, Jun. 2019.

[101] A. Zavodovski, S. Bayhan, N. Mohan, P. Zhou, W. Wong, and J. Kangasharju, "DeCloud: Truthful decentralized double auction for edge clouds," in *Proc. IEEE 39th Int. Conf. Distrib. Comput. Syst.*, Dallas, TX, USA, 2019, pp. 2157–2167.

[102] W. Sun, J. Liu, Y. Yue, and P. Wang, "Joint resource allocation and incentive design for blockchain-based mobile edge computing," *IEEE Trans. Wireless Commun.*, vol. 19, no. 9, pp. 6050–6064, Sep. 2020.

[103] A.-L. Jin, W. Song, P. Wang, D. Niyato, and P. Ju, "Auction mechanisms toward efficient resource sharing for cloudlets in mobile cloud computing," *IEEE Trans. Services Comput.*, vol. 9, no. 6, pp. 895–909, Nov./Dec. 2016.

[104] K. Xiao, W. Shi, Z. Gao, C. Yao, and X. Qiu, "DAER: A resource pre-allocation algorithm of edge computing server by using blockchain in intelligent driving," *IEEE Internet Things J.*, vol. 7, no. 10, pp. 9291–9302, Oct. 2020.

[105] M. He, N. R. Jennings, and A. Prugel-Bennett, "An adaptive bidding agent for multiple English auctions: A neuro-fuzzy approach," in *Proc. IEEE Int. Conf. Fuzzy Syst.*, vol. 3. Budapest, Hungary, 2004, pp. 1519–1524.

[106] W. Zhang, Y. Wen, K. Guan, D. Kilper, H. Luo, and D. O. Wu, "Energy-optimal mobile cloud computing under stochastic wireless channel," *IEEE Trans. Wireless Commun.*, vol. 12, no. 9, pp. 4569–4581, Sep. 2013.

[107] S. Barbarossa, S. Sardellitti, and P. Di Lorenzo, "Communicating while computing: Distributed mobile cloud computing over 5G heterogeneous networks," *IEEE Signal Process. Mag.*, vol. 31, no. 6, pp. 45–55, Nov. 2014.

[108] J. Feng, Z. Liu, C. Wu, and Y. Ji, "AVE: Autonomous vehicular edge computing framework with ACO-based scheduling," *IEEE Trans. Veh. Technol.*, vol. 66, no. 12, pp. 10660–10675, Dec. 2017.

[109] H.-J. Hong, W. Fan, C. E. Chow, X. Zhou, and S.-Y. Chang, "Optimizing social welfare for task offloading in mobile edge computing," in *Proc. IFIP Netw. Conf. (Networking)*, Paris, France, 2020, pp. 524–528.

[110] A. V. Goldberg, "An efficient implementation of a scaling minimum-cost flow algorithm," *J. Algorithms*, vol. 22, no. 1, pp. 1–29, 1997.

[111] S. Wang, H. Liu, P. H. Gomes, and B. Krishnamachari, "Deep reinforcement learning for dynamic multichannel access in wireless networks," *IEEE Trans. Cogn. Commun. Netw.*, vol. 4, no. 2, pp. 257–265, Jun. 2018.

[112] D. Zhao, H. Qin, B. Song, Y. Zhang, X. Du, and M. Guizani, "A reinforcement learning method for joint mode selection and power adaptation in the V2V communication network in 5G," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 2, pp. 452–463, Jun. 2020.

[113] M. H. Ling, K.-L. A. Yau, J. Qadir, and Q. Ni, "A reinforcement learning-based trust model for cluster size adjustment scheme in distributed cognitive radio networks," *IEEE Trans. Cogn. Commun. Netw.*, vol. 5, no. 1, pp. 28–43, Mar. 2019.

[114] Q. Li, H. Yao, T. Mai, C. Jiang, and Y. Zhang, "Reinforcement-learning- and belief-learning-based double auction mechanism for edge computing resource allocation," *IEEE Internet Things J.*, vol. 7, no. 7, pp. 5976–5985, Jul. 2020.

[115] V. L. Smith, "An experimental study of competitive market behavior," *J. Polit. Econ.*, vol. 70, no. 2, pp. 111–137, 1962.

[116] C. Camerer, T.-H. Ho, C. Camerer, and T. H. Ho, "Experience-weighted attraction learning in games: A unifying approach," Dept. Division Humanities Soc. Sci., California Inst. Technol., Pasadena, CA, USA, Rep., 1997.

[117] X. Peng, K. Ota, and M. Dong, "Multiattribute-based double auction toward resource allocation in vehicular fog computing," *IEEE Internet Things J.*, vol. 7, no. 4, pp. 3094–3103, Apr. 2020.

[118] H. W. Kuhn, "The Hungarian method for the assignment problem," *Naval Res. Log. Quart.*, vol. 2, nos. 1–2, pp. 83–97, 1955.

[119] J. Munkres, "Algorithms for the assignment and transportation problems," *SIAM J. Appl. Math.*, vol. 5, no. 1, pp. 32–38, 1957.

[120] D. Yang, X. Fang, and G. Xue, "Truthful auction for cooperative communications," in *Proc. 12th ACM Int. Symp. Mobile Ad Hoc Netw. Comput.*, 2011, pp. 1–10.

[121] X. Liu, J. Wu, L. Chen, and C. Xia, "Efficient auction mechanism for edge computing resource allocation in mobile blockchain," in *Proc. IEEE HPCC/SmartCity/DSS*, Zhangjiajie, China, 2019, pp. 871–876.

[122] S. Guo, Y. Dai, S. Guo, X. Qiu, and F. Qi, "Blockchain meets edge computing: Stackelberg game and double auction based task offloading for mobile blockchain," *IEEE Trans. Veh. Technol.*, vol. 69, no. 5, pp. 5549–5561, May 2020.

[123] C.-H. Liao, H.-E. Lin, and S.-M. Yuan, "Blockchain-enabled integrated market platform for contract production," *IEEE Access*, vol. 8, pp. 211007–211027, 2020.

[124] S. Wang *et al.*, "Blockchain-powered parallel healthcare systems based on the ACP approach," *IEEE Trans. Computat. Social Syst.*, vol. 5, no. 4, pp. 942–950, Dec. 2018.

[125] W. Liang, Y. Fan, K.-C. Li, D. Zhang, and J.-L. Gaudiot, "Secure data storage and recovery in industrial blockchain network environments," *IEEE Trans. Ind. Informat.*, vol. 16, no. 10, pp. 6543–6552, Oct. 2020.

[126] G. Zhou, J. Wu, and L. Chen, "TACD: A three-stage auction scheme for cloudlet deployment in wireless access network," in *Proc. 10th Int. Conf. Wireless Algorithms Syst. Appl. (WASA)*, 2017, pp. 877–882.

[127] P. Samimi, Y. Teimouri, and M. Mukhtar, "A combinatorial double auction resource allocation model in cloud computing," *Inf. Sci.*, vol. 357, pp. 201–216, Aug. 2016.

[128] S. Zou, Z. Ma, and X. Liu, "Resource allocation game under double-sided auction mechanism: Efficiency and convergence," *IEEE Trans. Autom. Control*, vol. 63, no. 5, pp. 1273–1287, May 2018.

[129] Z. Xiong, S. Feng, D. Niyato, P. Wang, and Z. Han, "Optimal pricing-based edge computing resource management in mobile blockchain," in *Proc. IEEE ICC*, Kansas City, MO, USA, 2018, pp. 1–6.

[130] X. Dong, Z. You, L. Wang, S. Gao, Y. Shen, and J. Ma, "A truthful online incentive mechanism for nondeterministic spectrum allocation," *IEEE Trans. Wireless Commun.*, vol. 19, no. 7, pp. 4632–4642, Jul. 2020.

[131] Y. Chen, P. Lin, and Q. Zhang, "LOTUS: Location-aware online truthful double auction for dynamic spectrum access," *IEEE Trans. Wireless Commun.*, vol. 14, no. 2, pp. 1092–1099, Feb. 2015.

[132] B. J. Ford, H. Xu, and I. Valova, "A real-time self-adaptive classifier for identifying suspicious bidders in online auctions," *Comput. J.*, vol. 56, no. 5, pp. 646–663, 2013.

[133] H. S. Du, H. Yu, Y. Fang, and S. Wang, "Empirical investigation of EachNet: The eBay model of C2C online auction in China," *IEEE Trans. Eng. Manag.*, vol. 59, no. 1, pp. 160–175, Feb. 2012.

[134] D. Li, Q. Yang, W. Yu, D. An, Y. Zhang, and W. Zhao, "Towards differential privacy-based online double auction for smart grid," *IEEE Trans. Inf. Forensics Security*, vol. 15, pp. 971–986, 2019.

[135] S. Wang, Z. Zhang, R. Yu, and Y. Zhang, "Low-latency caching with auction game in vehicular edge computing," in *Proc. IEEE/CIC*, Qingdao, China, 2017, pp. 1–6.

[136] J. He, D. Zhang, Y. Zhou, and Y. Zhang, "A truthful online mechanism for collaborative computation offloading in mobile edge computing," *IEEE Trans. Ind. Informat.*, vol. 16, no. 7, pp. 4832–4841, Jul. 2020.

[137] Q. Wang, S. Guo, J. Liu, C. Pan, and L. Yang, "Profit maximization incentive mechanism for resource providers in mobile edge computing," *IEEE Trans. Services Comput.*, vol. 15, no. 1, pp. 138–149, Jan./Feb. 2022.

[138] Y. Zhang, C.-Y. Wang, and H.-Y. Wei, "Parking reservation auction for parked vehicle assistance in vehicular fog computing," *IEEE Trans. Veh. Technol.*, vol. 68, no. 4, pp. 3126–3139, Apr. 2019.

[139] C. Zhou and C.-K. Tham, "Where to process: Deadline-aware online resource auction in mobile edge computing," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. Workshops (PerCom Workshops) IEEE Int. Conf. Pervasive Comput. Commun. Workshops (PerCom Workshops)*, 2018, pp. 675–680.

[140] F. Wang, C. Xu, L. Song, Z. Han, and B. Zhang, "Energy-efficient radio resource and power allocation for device-to-device communication underlaying cellular networks," in *Proc. IEEE Int. Conf. WCSP*, Huangshan, China, 2012, pp. 1–6.

[141] T. Roughgarden, "Algorithmic game theory," *Commun. ACM*, vol. 53, no. 7, pp. 78–86, 2010.

[142] D. P. Williamson and D. B. Shmoys, *The Design of Approximation Algorithms*. Cambridge, U.K.: Cambridge Univ. Press, 2011.

[143] X. Chen, L. Jiao, W. Li, and X. Fu, "Efficient multi-user computation offloading for mobile-edge cloud computing," *IEEE/ACM Trans. Netw.*, vol. 24, no. 5, pp. 2795–2808, Oct. 2016.

[144] Y. Geng and C. G. Cassandras, "New 'smart parking' system based on resource allocation and reservations," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 3, pp. 1129–1139, Sep. 2013.

[145] B. Zou, N. Kafle, O. Wolfson, and J. J. Lin, "A mechanism design based approach to solving parking slot assignment in the information era," *Transp. Res. B, Methodol.*, vol. 81, pp. 631–653, Nov. 2015.

[146] T. N. Pham, M.-F. Tsai, D. B. Nguyen, C.-R. Dow, and D.-J. Deng, "A cloud-based smart-parking system based on Internet-of-Things technologies," *IEEE Access*, vol. 3, pp. 1581–1591, 2015.

[147] T. Lin, H. Rivano, and F. Le Mouël, "A survey of smart parking solutions," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 12, pp. 3229–3253, Dec. 2017.

[148] X.-W. Wang, X.-Y. Wang, and M. Huang, "A resource allocation method based on the limited English combinatorial auction under cloud computing environment," in *Proc. 9th Int. Conf. Fuzzy Syst. Knowl. Discov. (FSKD)*, Chongqing, China, 2012, pp. 905–909.

[149] T. H. T. Le, N. H. Tran, Y. K. Tun, O. T. T. Kim, K. Kim, and C. S. Hong, "Sharing incentive mechanism, task assignment and resource allocation for task offloading in vehicular mobile edge computing," in *Proc. IEEE/IFIP Netw. Oper. Manag. Symp. (NOMS)*, Budapest, Hungary, 2020, pp. 1–8.

[150] U. Habiba, S. Maghsudi, and E. Hossain, "A reverse auction model for efficient resource allocation in mobile edge computation offloading," in *Proc. IEEE GLOBECOM*, Waikoloa, HI, USA, 2019, pp. 1–6.

[151] Q. Xu, Z. Su, Y. Wang, and M. Dai, "A trustworthy content caching and bandwidth allocation scheme with edge computing for smart campus," *IEEE Access*, vol. 6, pp. 63868–63879, 2018.

[152] R. Carr and S. Vempala, "Randomized metarounding," in *Proc. 22nd Annu. ACM Symp. Theory Comput.*, 2000, pp. 58–62.

[153] J. Li, Y. Zhu, Y. Hua, and J. Yu, "Crowdsourcing sensing to smartphones: A randomized auction approach," *IEEE Trans. Mobile Comput.*, vol. 16, no. 10, pp. 2764–2777, Oct. 2017.

[154] D. Gale and L. S. Shapley, "College admissions and the stability of marriage," *Amer. Math. Monthly*, vol. 69, no. 1, pp. 9–15, 1962.

[155] J. Sethuraman, C.-P. Teo, and L. Qian, "Many-to-one stable matching: Geometry and fairness," *Math. Oper. Res.*, vol. 31, no. 3, pp. 581–596, 2006.

[156] H. R. Varian, "Position auctions," *Int. J. Ind. Org.*, vol. 25, no. 6, pp. 1163–1178, 2007.

[157] M. Cary *et al.*, "Greedy bidding strategies for keyword auctions," in *Proc. 8th ACM Conf. Electron. Commerce*, 2007, pp. 262–271.

[158] K. Sowmya and R. P. Sundarraj, "Generalized second price auction for relatively ranked heterogeneous spot instances in the cloud," in *Proc. 5th Int. Conf. Adv. Comput.*, Chennai, India, 2013, pp. 304–310.

[159] Y. Quan and D.-W. Wang, "Keywords tender price selected in the generalized second price position auction," in *Proc. 24th CCDC*, Taiyuan, China, 2012, pp. 816–820.

[160] R. P. Leme and E. Tardos, "Pure and bayes-nash price of anarchy for generalized second price auction," in *Proc. IEEE 51st Annu. Symp. Found. Comput. Sci.*, Las Vegas, NV, USA, 2010, pp. 735–744.

[161] E. Sirin, B. Parsia, D. Wu, J. Hendler, and D. Nau, "HTN planning for Web service composition using SHOP2," *J. Web Semantics*, vol. 1, no. 4, pp. 377–396, 2004.

[162] M. Chen, Y. Miao, H. Gharavi, L. Hu, and I. Humar, "Intelligent traffic adaptive resource allocation for edge computing-based 5G networks," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 2, pp. 499–508, Jun. 2020.

[163] J. Oksanen, B. Kaufman, V. Koivunen, and H. V. Poor, "Robotics inspired opportunistic routing for cognitive radio using potential fields," *IEEE Trans. Cogn. Commun. Netw.*, vol. 1, no. 1, pp. 45–55, Mar. 2015.

[164] M. Jia, J. Cao, and W. Liang, "Optimal cloudlet placement and user to cloudlet allocation in wireless metropolitan area networks," *IEEE Trans. Cloud Comput.*, vol. 5, no. 4, pp. 725–737, Oct.–Dec. 2017.

[165] D. Bermbach, S. Maghsudi, J. Hasenburg, and T. Pfandzelter, "Towards auction-based function placement in serverless fog platforms," in *Proc. IEEE Int. Conf. Fog Comput.*, Sydney, NSW, Australia, 2020, pp. 25–31.

[166] Q. Wang, S. Guo, Y. Wang, and Y. Yang, "Incentive mechanism for edge cloud profit maximization in mobile edge computing," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Shanghai, China, 2019, pp. 1–6.

[167] K. Zhu, Y. Xu, J. Qian, and D. Niyato, "Revenue-optimal auction for resource allocation in wireless virtualization: A deep learning approach," *IEEE Trans. Mobile Comput.*, early access, Sep. 3, 2020, doi: 10.1109/TMC.2020.3021416.

[168] N. C. Luong, Z. Xiong, P. Wang, and D. Niyato, "Optimal auction for edge computing resource management in mobile blockchain networks: A deep learning approach," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Kansas City, MO, USA, 2018, pp. 1–6.

[169] L. Li, T. Q. S. Quek, J. Ren, H. H. Yang, Z. Chen, and Y. Zhang, "An incentive-aware job offloading control framework for multi-access edge computing," *IEEE Trans. Mobile Comput.*, vol. 20, no. 1, pp. 63–75, Jan. 2021.

[170] A. Kiani and N. Ansari, "Toward hierarchical mobile edge computing: An auction-based profit maximization approach," *IEEE Internet Things J.*, vol. 4, no. 6, pp. 2082–2091, Dec. 2017.

[171] D. Justice and A. Hero, "A binary linear programming formulation of the graph edit distance," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 8, pp. 1200–1214, Aug. 2006.

[172] R. B. Myerson, "Optimal auction design," *Math. Oper. Res.*, vol. 6, no. 1, pp. 58–73, 1981.

[173] Y. Liu, C. Xu, Y. Zhan, Z. Liu, J. Guan, and H. Zhang, "Incentive mechanism for computation offloading using edge computing: A Stackelberg game approach," *Comput. Netw.*, vol. 129, pp. 399–409, Dec. 2017.

[174] Z. Gao, C. Yao, K. Xiao, Z. Mo, Q. Wang, and Y. Yang, "A real-time task offloading strategy based on double auction for optimal resource allocation in edge computing," in *Proc. 7th Int. Conf. Future Internet Things Cloud (FiCloud)*, Istanbul, Turkey, 2019, pp. 9–16.

[175] T. W. Sandholm, "Limitations of the Vickrey auction in computational multiagent systems," in *Proc. 2nd ICMAS*, 1996, pp. 299–306.

[176] M. Lee, Y. Xiong, G. Yu, and G. Y. Li, "Deep neural networks for linear sum assignment problems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 6, pp. 962–965, Dec. 2018.

[177] M. Lee, G. Yu, and G. Y. Li, "Learning to branch: Accelerating resource allocation in wireless networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 1, pp. 958–970, Jan. 2020.

[178] W. Y. B. Lim, J. S. Ng, Z. Xiong, D. Niyato, C. Miao, and D. I. Kim, "Dynamic edge association and resource allocation in self-organizing hierarchical federated learning networks," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 12, pp. 3640–3653, Dec. 2021.

[179] Q. Hu, S. Wang, Z. Xiong, and X. Cheng, "Nothing wasted: Full contribution enforcement in federated edge learning," *IEEE Trans. Mobile Comput.*, early access, Oct. 27, 2021, doi: 10.1109/TMC.2021.3123195.

[180] J. Nie, J. Luo, Z. Xiong, D. Niyato, and P. Wang, "A Stackelberg game approach toward socially-aware incentive mechanisms for mobile crowdsensing," *IEEE Trans. Wireless Commun.*, vol. 18, no. 1, pp. 724–738, Jan. 2019.

[181] R. Zeng, S. Zhang, J. Wang, and X. Chu, "FMore: An incentive scheme of multi-dimensional auction for federated learning in MEC," in *Proc. IEEE 40th Int. Conf. Distrib. Comput. Syst. (ICDCS)*, Singapore, 2020, pp. 278–288.

[182] S. Fan, H. Zhang, Y. Zeng, and W. Cai, "Hybrid blockchain-based resource trading system for federated learning in edge computing," *IEEE Internet Things J.*, vol. 8, no. 4, pp. 2252–2264, Feb. 2021.

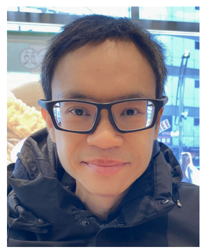
[183] H. Lee, S. Park, J. Kim, and J. Kim, "Auction-based deep learning computation offloading for truthful edge computing: A Myerson auction approach," in *Proc. Int. Conf. Inf. Netw.*, Jeju Island, South Korea, 2021, pp. 457–459.

Houming Qiu received the M.E. degree from the Institute of Information and Control, Hangzhou Dianzi University, Hangzhou, China, in 2018. He is currently pursuing the Ph.D. degree with the College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, Nanjing, China. His research interests include distributed computing, auction theory, coding theory, and edge computing.

Kun Zhu (Member, IEEE) received the Ph.D. degree from the School of Computer Engineering, Nanyang Technological University, Singapore, in 2012. He was a Research Fellow with the Wireless Communications Networks and Services Research Group, University of Manitoba, Canada, from 2012 to 2015. He is currently a Professor with the College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, China. His research interests include resource allocation in 5G, wireless virtualization, and self-organizing networks.

Nguyen Cong Luong received the B.S. degree in electronic and telecommunication engineering from the Hanoi University of Science and Technology. His research interest includes the next generation networks.

Changyan Yi (Member, IEEE) received the Ph.D. degree from the Department of Electrical and Computer Engineering, University of Manitoba, Winnipeg, MB, Canada, in 2018. He is currently a Professor with the College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics. From September 2018 to August 2019, he worked as a Research Associate with the University of Manitoba. His research interests include game theory, queueing theory, machine learning and their applications in various wireless networks including edge/fog computing, IoT, 5G, and beyond.



Dusit Niyato (Fellow, IEEE) received the B.Eng. degree from the King Mongkuts Institute of Technology Ladkrabang, Thailand, in 1999, and the Ph.D. degree in electrical and computer engineering from the University of Manitoba, Canada, in 2008. He is currently a Professor with the School of Computer Science and Engineering, Nanyang Technological University, Singapore. His research interests are in the areas of Internet of Things, machine learning, and incentive mechanism design.

Dong In Kim (Fellow, IEEE) received the Ph.D. degree in electrical engineering from the University of Southern California, Los Angeles, CA, USA, in 1990. He has been listed as a 2020 Highly Cited Researcher by Clarivate Analytics. He was selected as the 2019 recipient of the IEEE Communications Society Joseph LoCicero Award for Exemplary Service to Publications. He is also the General Chair for the IEEE International Conference on Communications 2022 in Seoul. From 2001 to 2020, he has served as an Editor and an Editor-at-Large of Wireless Communications I for IEEE TRANSACTIONS ON COMMUNICATIONS. He has served as the Founding Editor-in-Chief for IEEE WIRELESS COMMUNICATIONS LETTERS from 2012 to 2015.