Making Knowledge Tradable in Edge-AI Enabled IoT: A Consortium Blockchain-Based Efficient and Incentive Approach

Xi Lin, *Student Member, IEEE*, Jianhua Li, Jun Wu, *Member, IEEE*, Haoran Liang, and Wu Yang

***Abstract*—Nowadays, benefit from more powerful edge computing devices and edge artificial intelligence (edge-AI) could be introduced into Internet of Things (IoT) to find the knowledge derived from massive sensory data, such as cyber results or models of classification, and detection and prediction from physical environments. Heterogeneous edge-AI devices in IoT will generate isolated and distributed knowledge slices, thus knowledge collaboration and exchange are required to complete complex tasks in IoT intelligent applications with numerous selfish nodes. Therefore, knowledge trading is needed for paid sharing in edge-AI enabled IoT. Most existing works only focus on knowledge generation rather than trading in IoT. To address this issue, in this paper, we propose a peer-to-peer (P2P) knowledge market to make knowledge tradable in edge-AI enabled IoT. We first propose an implementation architecture of the knowledge market. Moreover, we develop a knowledge consortium blockchain for secure and efficient knowledge management and trading for the market, which includes a new cryptographic currency knowledge coin, smart contracts, and a new consensus mechanism proof of trading. Besides, a noncooperative game based knowledge pricing strategy with incentives for the market is also proposed. The security analysis and performance simulation show the security and efficiency of our knowledge market and incentive effects of knowledge pricing strategy. To the best of our knowledge, it is the first time to propose an efficient and incentive P2P knowledge market in edge-AI enabled IoT.**

***Index Terms*—Consortium blockchain, edge artificial intelligence (edge-AI), Internet of Things (IoT), knowledge market, knowledge pricing, smart contract.**

I. Introduction

WITH the rapid growth of big data generated by Internet of Things (IoT) at the edge of networks, the data

Manuscript received April 20, 2019; accepted May 7, 2019. Date of publication May 16, 2019; date of current version December 3, 2019. This work was supported by the National Natural Science Foundation of China under Grant 61431008 and Grant 61831007. Paper no. TII-19-1471. *(Corresponding author: Jun Wu.)*

X. Lin, J. Li, J. Wu, and H. Liang are with the School of Cyber Security and the Shanghai Key Laboratory of Integrated Administration Technologies for Information Security, Shanghai Jiao Tong University, Shanghai 200240, China (e-mail: linxi234@sjtu.edu.cn; lijh888@sjtu.edu.cn; junwuhn@sjtu.edu.cn; hrliang@sjtu.edu.cn).

W. Yang is with Information Security Research Center, Harbin Engineering University, Harbin 165001, China (e-mail: yangwu@hrbeu.edu.cn).

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Digital Object Identifier 10.1109/TII.2019.2917307

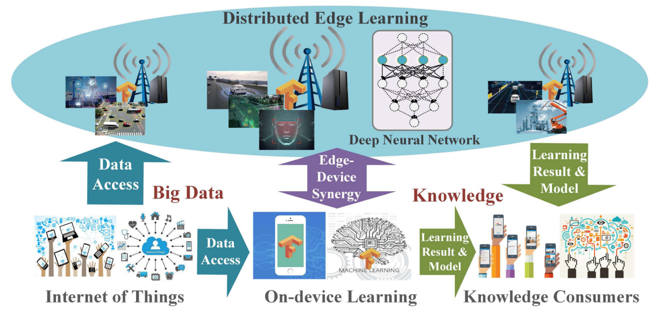

Fig. 1. Architecture of edge-AI enabled IoT.

generation rate will exceed the capacity of Internet in the near future. Thus, over 90% of the IoT big data will be handled and analyzed locally rather than remote clouds [1]. As the complement of clouds, edge (or fog) computing brings cloud-like computation resources to local edge nodes [2], [3]. Meanwhile, artificial intelligence (AI) services are being deployed on the edge computing platform for IoT applications, earning the nickname of edge artificial intelligence (edge-AI) [4], [5]. Therefore, as shown in Fig. 1, mobile edge computing (MEC) enhanced base stations BSs (distributed edge learning) and powerful distributed edge devices (on-device learning) make it possible for local knowledge extraction from massive IoT data. Therefore, IoT service mode will be gradually transformed from "Data-as-a-Service" [6] to "Knowledge-as-a-Service" [7].

Knowledge is the real value of data, which includes learning results and models derived from IoT data. For example, surveillance cameras with edge-AI can carry out real-time data analysis and detecting and tracking a specific person via face recognition. The detection results (knowledge) rather than massive redundant video data could be paid sharing. The trained learning models should also be monetized as knowledge commodities (KCs). For instance, the Algorithmia trading marketplace [8] hosts a library of about 4500 trained models application programming interface (API) for image classification, language translation, etc.

In edge-AI enabled IoT, better intelligent applications depend on knowledge collaboration and exchange among edge-AI devices. For the isomorphic IoT knowledge, an edge-AI device cannot collect all the relevant data resulting from the geographical distribution manner. Such as intelligent monitoring, a single camera can only analyze data within a certain spatio-temporal range. The detection results (knowledge slices) for all cameras should be sharing to constitute complement knowledge for other devices or users. Another example was proposed in [4], for distributed data analysis, distributed learning models hold by 100 edge devices are sharing to one edge server for federated learning, generating a global learning model. On the other hand, for the heterogeneous IoT knowledge, due to the resource-constrained feature of edge-AI, it is impractical and unnecessary to cache all AI services on an edge device at the same time [9]. For instance, a smart camera with face recognition cannot perform voice recognition, such as an intelligent sound box. The heterogeneous knowledge acquisition must rely on collaboration and exchange. To sum up, sharing knowledge among edge-AI entities is essential to achieve large-scale distributed performance optimization in edge-AI enabled IoT.

However, due to the existing heterogeneity (spatio-temporal, entity, and relation) of IoT data resources, the acquired knowledge derived from data is mastered in a variety of edge-AI entities. They may be reluctant to cooperate with each other, due to the selfishness and distrust, which are as follows.

1) Knowledge sharing should be reasonable monetized to motivate knowledge paid sharing for selfish edge-AI entities.
2) Knowledge trading should be in a distributed peer-to-peer (P2P) mode rather than an unrealistic and inefficient centralized mode, considering the large-scale geographical distribution of numerous edge-AI devices.
3) Knowledge market should guarantee the security and privacy of all the market participants, such as avoiding malicious users tamper the relevant knowledge bases. These challenges have seriously slowed down the pace for development of knowledge sharing in edge-AI enabled IoT.

Recently, blockchain, an open decentralized ledger-based distributed technology, causes widespread concerns in both academia and industry. It was first applied into a P2P e-cash system *Bitcoin* [10] by Nakamoto. Then, benefit from the good properties of tamper-resistance, transparency, and trust, blockchain-based applications have already gained great popularity in cognitive wireless networks, smart grid [12], vehicular ad hoc networks (VANETs) [13], and IoT. In general, blockchain can establish an Internet of value, where participants could store and exchange value without traditional intermediaries. Therefore, motivated by previous works, we exploit the blockchain technologies (consortium blockchain/smart contract) and game theory to build a knowledge market, for achieving knowledge cooperation and exchange in edge-AI enabled IoT. The contributions of this paper are summarized as follows.

1) We proposed a secure and efficient P2P knowledge market in edge-AI enabled IoT. To the best of our knowledge, it is the first time to propose a knowledge paid sharing architecture in edge-AI enabled IoT.
2) We exploit blockchain technologies (consortium blockchain/smart contract) to establish a knowledge blockchain for the market to ensure knowledge management and trading decentralization, nontampering, efficient automation, and fairness.
3) We proposed a new green blockchain consensus mechanism Proof of Trading PoT that required less resource consumption combining Proof-of-Work (PoW) with Proof-of-Stake (PoS) mechanism.
4) We proposed a noncooperative game based optimal knowledge pricing strategy for the knowledge market. Numerical results show this strategy encourages knowledge sellers to provide higher quality knowledge under the same budget.

The remainder of this paper is structured as follows. Section II gives an overview of the related works. Section III describes the proposed knowledge market architecture in edge-AI enabled IoT. Section IV introduces the knowledge blockchain design for the market. In Section V, a noncooperative game based knowledge pricing strategy with incentives is proposed. In Section VI, we analyze the security performance and provide the simulation results. Finally, Section VII concludes this paper.

II. Related Work

Market economy models [14] have been widely applied in IoT systems for trading data/information goods from physical environment. In [15], Perera *et al.* explored the data marketplace with the concept of "Sensing as a Service" and its advantages in IoT-enabled smart cities. To realize a fast, secure, and reliable data transfer, a framework for cloud-based pervasive IoT applications was proposed in [16]. For minimizing the data retrieval time, Xie and Jia developed a max-throughput data transfer scheduling in [17]. While the authors in [18] and [19] pay more attention to pricing mechanisms, a data procurement auction in Bayesian setting achieving both strategy-proofness and optimal payment was developed in [18], and the benefits of traded data plans for mobile data in secondary data markets were studied in [19]. Besides, an information market approach with price competition was introduced to IoT in [20], and specifically, the authors in [21] investigated the information pricing in cognitive radio networks by two-stage Stackelberg game. However, most of the previous works only focused on IoT data/information market, whereas knowledge market in IoT still remains blank.

Knowledge is the further refinement of data/information, natural or artificial, which is the root of intelligence. Recently, edge intelligence has been put into IoT systems [4], [5], [7]. In [7], a knowledge-centric edge cellular network architecture was designed with virtualized device-to-device (D2D) communication and Li *et al.* in [22] presented an Edgent framework as a collaborative and on-demand deep neural network coinference with device-edge synergy. In specific, to jointly optimize caching and computing allocation problem in VANET, a mobility aware algorithm using both particle swarm optimization and deep Q-learning was proposed in [23], and in [24], the authors also implemented an online user activity recognition engine based on edge intelligence with high real-time and fault-tolerance performance. However, those works just concentrated on general edge-AI enabled IoT architectures or how to generate specific IoT knowledge via AI algorithms, whereas the great potential of the knowledge market economy has been neglected.

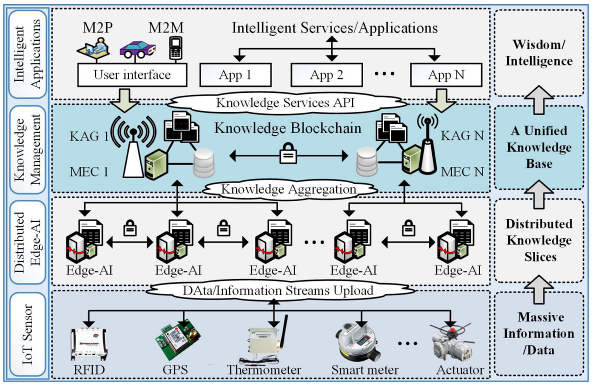

Fig. 2. Basic architecture of the proposed knowledge market.

III. Knowledge Market in Edge-AI Enabled IoT

A. Basic Architecture of Proposed Knowledge Market

As shown in Fig. 2, the basic architecture of proposed knowledge market consists of several planes: the IoT sensor plane, distributed edge-AI plane, knowledge management plane, and intelligent applications plane. The architecture can implement the process from data/information to knowledge to intelligence/wisdom.

The sensor plane consists of underlying infrastructure in IoT (e.g., GPS, radio frequency identification, thermometer, etc). The massive sensory data/information streams are periodically uploaded to edge-AI devices for storing and processing. AI algorithms (support vector machine (SVM), deep learning, etc) are deployed in the distributed edge-AI plane, which contain more powerful geodistributed edge-AI devices, such as mobile phones, unmanned aerial vehicles, smart vehicles, IoT intelligent sensors/gateways, and microservers (Raspberry Pi), offering temporary storage, computing, and communication resources for knowledge discovery, creation, and exchange. Therefore, edge-AI devices are knowledge producers of our knowledge market. The knowledge aggregators (KAGs) in the knowledge management plane are enhanced BSs with better resources, such as small cell or macrocell, which aggregate discrete knowledge slices from edge-AI devices in corresponding areas. Besides, upstream KAGs are preselected nodes for maintaining consortium knowledge blockchain platform, which forms a unified knowledge base at the edge of networks and implements distributed P2P knowledge trading. So, we name them KAGs in this paper. The intelligent application plane includes a series of knowledge-based intelligent services/applications, such as intelligent alarm system, intelligent manufacturing, intelligent transportation system, etc. With the APIs, users can publish their knowledge requests to knowledge blockchain and reward relevant knowledge contributors via economics.

In our knowledge market, edge-AI entities can share the acquired knowledge with corresponding returns, called knowledge coins. It is a new cryptographic currency slightly similar to BTC and Ether (ETC) used in *Bitcoin* and *Ethereum* [11], respectively. The knowledge market is composed of the following elements.

1) *Trusted authority (TA):* TA can be a government department, which is responsible for initializing the whole knowledge trading market. TA can generate public parameters and cryptographic keys for market participants. After registration on a TA, edge-AI nodes and KAGs could be legitimate members.
2) *Edge-AI nodes:* Edge-AI nodes in IoT could act as different roles according to their states: knowledge seller, knowledge buyer, or idle node. An edge-AI node could act as a seller after discovering knowledge from collected sensory data or after receiving the knowledge requests. It would upload the encrypted knowledge to knowledge managers (KAGs). Knowledge is not public in the market. A knowledge buyer would find the diverse knowledge of interests in the market. When the knowledge is acquired, the relevant knowledge coins should be paid as economic returns immediately. Idle nodes neither provide nor purchase KCs in the market.
3) *Knowledge aggregators:* As shown in [25], nowadays, BS density in cellular networks has kept increasing in 4G networks and will reach around 50 BSs/km2 in the next 5G networks. Integrating MEC into BSs ultradense networks is future trends [26]. It indicates that each BS will be equipped with better 3C (cache, computation, and communication) resources. BSs are usually connected through high-speed wired networks. Therefore, apart from being edge-AI nodes, they could serve as knowledge managers (KAGs) in the market. They could store and manage the uploading encrypted KCs and record the knowledge trading information. Meanwhile, they also have the responsibility to ensure the security and privacy of the knowledge market.

B. Design Goals for Proposed Knowledge Market

As an available knowledge market, we not only need to ensure security and efficiency, but the interests of all participants should also be taken into consideration. Therefore, the design of the knowledge market should realize the goals as follows.

1) Knowledge decentralization: Due to the geographical distribution of a large number of edge-AI devices, centralized knowledge management is unrealistic and inefficient. So, for the availability and reliability of our system, decentralized knowledge management should be realized.
2) Knowledge nontampering: KC is stored in KAGs, which could be attacked by malicious attackers. In the compromised KAGs, malicious attackers could tamper the KCs and trading records. Knowledge integrity and nontampering should be guaranteed.
3) Knowledge confidentiality: Resulting from knowledge paid sharing, knowledge is not public in the market. All participants (including KAGs) in the market could not obtain the uploading knowledge without rewarding. So, KCs exist in the KAGs in an encrypted manner.
4) Knowledge fairness: The nonrepudiation of knowledge trading is the key to realize the fairness. The buyers

obtain KCs once the knowledge coins are paid, whereas sellers get the corresponding returns once revealing the encrypted commodities for buyers. Besides, KAGs with more contributions for knowledge management and trading need to be rewarded with more financial returns as incentives.

5) Knowledge pricing: Reasonable knowledge pricing is the foundation of the market, directly affecting the development of our knowledge market. So, an optimal knowledge pricing strategy should be obtained, taking into account the interests of both parties.

IV. Knowledge Blockchain for Proposed Market

Blockchain, as a distributed management technology, has the potential to achieve design goals in our market (e.g., knowledge decentralization and knowledge nontampering). So, we design a knowledge blockchain (K-chain) for our market, which consists of the following components.

1) *Consortium blockchain:* Public blockchain and consortium (or private) blockchain are two existing forms of the blockchain. For public blockchain, some edge devices cannot meet the resources requirements, such as PoW. Besides, for public blockchain, the large number of edge-AI devices makes trading verification poor efficiency. Compared with public blockchain, trading verification in consortium blockchain only needs preselected high-power nodes (KAGs), with smaller costs and high efficiency [12]. Therefore, we utilize consortium blockchain to establish our knowledge trading market platform. Other edge-AI nodes could join the blockchain network via nearby KAGs with permission.
2) Proof of trading: For serving more edge applications, even KAGs cannot spend too many computation/energy resources to calculate the meaningless hash nonce for PoW consensus mechanism. Thus, the traditional PoW protocol is not applicable at the edge of networks. Meanwhile, KAGs with more contributions need to be rewarded (e.g., easier to solve the hash puzzle). So, a new consensus mechanism PoT is proposed in the knowledge blockchain joint considering KAGs' market interests and resource consumption.
3) Smart contract: We also employ smart contracts residing in the blockchain system in this paper to further improve the efficiency of the system. Smart contracts are scripts, which enable the automatic execution of multiphase processes. Once executed, smart contracts cannot be modified and interrupted. Knowledge management smart contract (KMSC) and knowledge trading smart contract (KTSC) are two existing smart contracts in our market, which make knowledge management and trading more reliable and efficient. Besides, KTSC can guarantee the fairness of knowledge trading, benefit from the nonrepudiation of smart contracts.

A. Overview of the Proposed Knowledge Blockchain

As shown in Fig. 3, our K-chain can be divided into two subchains, i.e., knowledge management chain (KM-chain) and knowledge trading chain (KT-chain) in edge-AI enabled IoT. They are responsible for knowledge management and knowledge trading in the market, respectively.

1) Knowledge Management: KM-chain needs to manage KCs from knowledge sellers. As shown in Fig. 3, KM-chain contains the KMSC contract and Proof of Capacity (PoC) mechanism. KAGs first collect all the uploaded KCs within their coverage and generate knowledge blocks. After the PoC-based consensus process, knowledge blocks will be broadcast to all KAGs and added to the KM-chain. Thus, a unified nontamperable edge knowledge base management could be realized. Besides, KMSC will be deployed in KM-chain to realize the automation of knowledge management.

2) Knowledge Trading: Knowledge trading process will resort to the KT-chain, which includes the KTSC contract and PoT mechanism, as shown in Fig. 3. Potential knowledge buyers will search for KCs or services of interest in the market. Then, they will initiate knowledge requests to sellers. The buyers can reveal the uploaded encrypted commodities after the payment. The transaction records (TXs) will be put into transaction blocks, which will be added to KT-chain after the PoT-based consensus process. Moreover, multiphases of the trading process are also automatic by the KTSC script to ensure knowledge trading efficiency and fairness.

The KCs and TXs are special data, which could be stored in the block body in the form of the Merkel tree structure, as shown in Fig. 4. Similar to the *Bitcoin* system, we use it to concatenate the TXs and KCs in each transaction block and knowledge block, respectively. This structure can summarize quickly and validate the integrity of large-scale data. Therefore, any attempts to tamper with the TXs and KCs will be detected, which guarantee the tamper-proof characteristic.

B. Knowledge Management by KMSC

The knowledge management process using KMSC contains a few phases for KM-chain, which are as follows.

Phase 1. Market initialization: In the market, edge-AI nodes willing to provide KCs or services could act as knowledge sellers. TA will evaluate the service capabilities of sellers. After being authorized by TA, a seller becomes a legitimate merchant in the knowledge market. To further protect the privacy of sellers, a seller with the true ID_i will obtain m pseudonyms' identities $\{\mathrm{PID}_i^k\}_{k=1}^m$ and corresponding asymmetric keys$\{PK_{\mathrm{PID}_i}^k, SK_{\mathrm{PID}_i}^k\}$/certificates $\{\mathrm{Cert}_{\mathrm{PID}_i}^k\}$ from TA. The asymmetric keys are employed to encrypt KCs to guarantee knowledge confidentiality in the market. Similar to sellers, the buyers also use pseudonyms' identities from TA. Besides, each participant will have a wallet account to manage their knowledge coins just as in [12].

Phase 2. Generating knowledge service indexes: For sellers, service-types and parameters may change dynamically over time in the market. So, the newest knowledge service indexes will be periodically uploaded to KM-chain platform. The knowledge service information is public in the market for buyers' reference as listed in Table I.

Phase 3. Generating KCs: If sellers discover knowledge from collected data. The acquired KCs will be uploaded to the

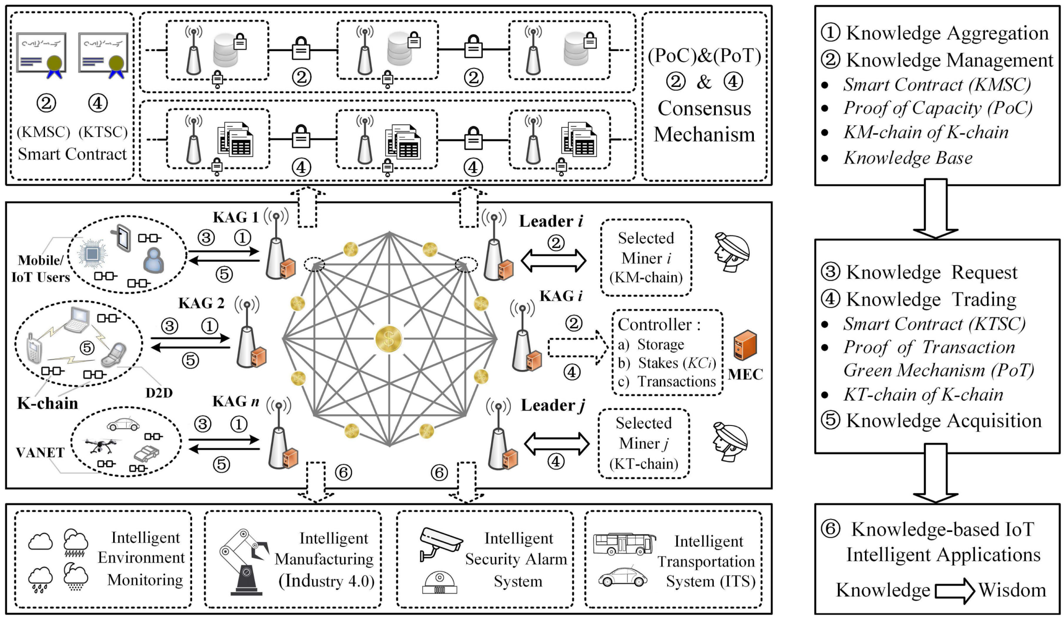

Fig. 3. Knowledge blockchain in our knowledge market.

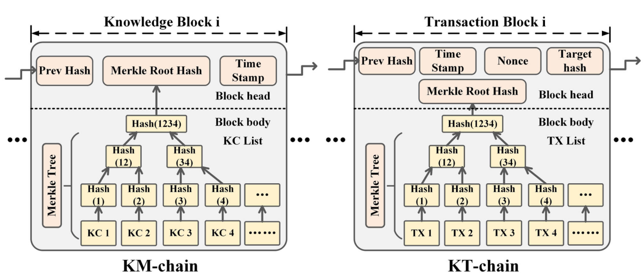

Fig. 4. Merkel hash tree structure of blocks.

TABLE I
KNOWLEDGE SERVICE INFORMATION

Knowledge Service Index	
Seller/KAG ID	Timestamp
Service Types	Learning Cost
$(1, 2, 3, ..., i)$	$(C_1, C_2, ..., C_i)$
Learning Ability	Minimum Utility
$(\theta_1^{th}, \theta_2^{th}, ..., \theta_i^{th})$	$(U_1^{th}, U_2^{th}, ..., U_i^{th})$

TABLE II
KNOWLEDGE COMMODITY

Knowledge Commodity *ID*	
Seller/KAG *ID*	Timestamp
Knowledge Ciphertext	Knowledge Type
Knowledge Pricing	Knowledge Value
Learning Data Sources	Learning Data Amount

KM-chain in an encrypted manner. We assume the seller s_i has KC π_j. Then, the seller will encrypt π_j with the seller pseudonym's public key $E_{PK_{s_i}}(\pi_i \| \text{Timestamp})$. The KC is listed in Table II.

Phase 4. Uploading knowledge information: Knowledge information from sellers consists of knowledge service indexes and KCs. Then, knowledge information will be uploaded to the nearby KAGs. The knowledge information can be browsed and queried in the market. Specifically, a seller first sends an uploading request to the nearby KAG, including being used PID_i, corresponding signature, and certificate. If the request is allowed, the seller can participate in knowledge market through publishing available services information and KCs.

Phase 5. Proof of capacity: Each KAG is equipped with a local controller. It is responsible for recording the storage contribution of each KAG about knowledge management. As

TABLE III
KEY SYMBOLS AND EXPLAINS

Symbols	Explains
KS_{i_total}	The periodic stake of miner KAG i in PoT consensus mechanism.
$target_i$	The hash puzzle target for miner KAG i in PoT/PoW consensus mechanism.
E_i	The expectation of computation resources of PoT/PoT consensus mechanism.
$D(.)$	Demand proportion functions of requested heterogeneous knowledge of buyers.
π_{ij}	The ith isomorphic knowledge from jth knowledge seller.
B_i	Total budget for ith isomorphic knowledge.
θ_{ij}	The learning data size of knowledge π_{ij} from jth knowledge seller.
$\psi_{\pi_{ij}}(\theta_{ij})$	The knowledge value function of knowledge from jth knowledge seller.
C_{ij}	The learning and data purchasing cost of knowledge π_{ij} from jth knowledge seller.
U_{ij}	The utility function of each knowledge sellers about knowledge π_{ij}.
θ_{ij}^{th}	The maximum and minimum learning ability of the seller about knowledge π_{ij}.
P_{ij}	The optimal knowledge pricing strategy for the seller about knowledge π_{ij}.

shown in Fig. 3, a certain KAG could be a leader *i* (e.g., selected miner for KM-chain), who contribute the most storage capacity for a period of time. The leader *i* has privilege to broadcast the new knowledge block. It is known as PoC. Meanwhile, leader *i* will be awarded by knowledge coins attached to the knowledge block. Generated knowledge block will be broadcast to all the KAG nodes for audit and verification. If other KAGs agree on this knowledge block, it will be added to KM-chain. Thus, due to the tamper-proof property of blockchain, cross-regional secure knowledge management is achieved.

C. Knowledge Trading by KTSC

The detail process of knowledge trading in the proposed market employing KTSC smart contract is described as the following phases.

Phase 1. Knowledge service requesting: Knowledge buyers will first search for their knowledge of interests in the market. If they do not find the needed knowledge. Knowledge buyers (edge-AI devices or users) will search for the knowledge services of interests via nearby KAGs. Then, they will choose a certain number of knowledge sellers according to the learning costs. Sellers with relatively low learning costs are expected to be chosen. The number of selected sellers will be slightly more than the actual sellers, in case of denial of services.

Phase 2. Knowledge pricing and depositing: Buyer b_r sends service requests to sellers, which include time, certificate of b_r, and request service types, etc. After receiving requests, sellers $s_1, s_2, \ldots, s_l$ verify the identity of the buyer b_r, and decide whether to provide knowledge services according to current states. Then, reply a result. According to knowledge service indexes of final service providers, buyer calculates the optimal knowledge pricing P_{ij} for final sellers. More detail about it will be shown in Section V. Meanwhile, the buyer needs to deposit budget $B = \sum P_{ij}$ to K-chain for each seller. Upon receiving the knowledge service deposits, KAG will check whether the buyer has enough knowledge coins in his wallet and send the deposit information to each seller.

Phase 3. KCs aggregating: After receiving the knowledge service requests and the deposit information, sellers provide knowledge services according to the pricing P_{ij}. Then, they use pseudonyms' public keys to encrypt the obtain knowledge and upload KCs via KMSC. The KCs will be stored in KM-chain platform.

Phase 4. Knowledge acquiring: To claim payment from the buyer, all the sellers will use the pseudonyms' public key of the buyer to encrypt the corresponding pseudonyms' private keys to generate the knowledge sharing, which is employed to decrypt KCs. The knowledge sharing will be uploaded to the nearby KAGs. If the buyer and the sellers belong to the same KAG, the knowledge sharing will be sent directly to the buyer, if not, the knowledge sharing will be sent to a KAG nearby the buyer. The KAG nearby the buyer will collect and send all the KCs and the knowledge sharing for the buyer. So, the buyer can harvest the knowledge of interests in the knowledge market.

Phase 5. Knowledge trading recording: After harvesting the knowledge from the market, the deposits will be paid to sellers automatically as knowledge rewards. If the sellers do not offer the knowledge sharing, the deposits will be aborted by KTSC. Only when the sellers provide the knowledge sharing, the deposits will be rewarded to sellers. As shown in Fig. 3, the total amount of knowledge trading currency (e.g., knowledge coins flow) for a certain KAG *i* in a period of time can be calculated by the local controller as its stake. A certain KAG could be a leader *j*, who act as the fastest miner to solve the dynamic hash puzzle in PoT mechanism. After finding the hash random nonce value, leader *j* will broadcast the block to all KAGs for audit and verification. Other KAGs will check the validity of the finding nonce and then this block will be added to KT-chain.

If the buyer finds the needed KCs at the phase 1, the trading process will be simpler. The buyer will deposit payment according to the given price information attached to KCs. Then, the trading process is similar as mentioned above.

D. PoT Consensus Mechanism

PoW mechanism is utilized in *Bitcoin* [10] by Nakamoto. The participants are required to contribute computation power to find a conditional hash random nonce. In KT-chain, the hash puzzle of PoW mechanism is given as

$$\begin{aligned}&\mathrm{Hash}(\mathrm{ID}_{\mathrm{KAG}_i}, \mathrm{Timestamp}, \mathrm{Hash}(\mathrm{previousdata}), \mathrm{nonce})\\ &\qquad \leq \mathrm{target}_{i\_\mathrm{PoW}} = 2^{N_{i\_\mathrm{PoW}}} - 1 \quad (1)\end{aligned}$$

where $\mathrm{target}_{i\_\mathrm{PoW}}$ is a string of binary bits, beginning from a number of continuous zeros. The number of $\mathrm{target}_{i\_\mathrm{PoW}}$ bits depends on different hash functions (MD5 for 16 B/128 b and SHA-256 for 32 B/256 b). For instance, the *Bitcoin* system employs the classical SHA-256 hash algorithm. According to (1), the smaller the target_i, the more difficult for solving the hash puzzle.

PoW leads to huge computation costs and energy consumption. So, it is not applicable to our design. Moreover, PoS is another consensus mechanism, which means the greater the stake, the greater the probability of publishing the next block. Although getting rid of too much waste of resources, pure PoS mechanism faces security vulnerability, such as nothing-at-stake attack and long-range attack.

In our knowledge market, knowledge trading managers (KAGs), as bridges between buyers and sellers, should give their proof of facilitating successful knowledge trading rather than solving a pure hash puzzle. Therefore, inspired by previous works, we propose a novel consensus mechanism PoT combining PoW with PoS mechanism. For a certain KAG *i*, we take the total amount of knowledge trading currency (e.g., knowledge coins) as its stake for a period of time. Due to openness of blockchain trading records, knowledge coins flow can be calculated by local controller. We dynamically adjust the difficulty of the hash puzzle according to KAGs' stakes. For KAG *i*, TX_{ij} and KS_{ij} indicate all the deals *j* and corresponding knowledge coins for a period of time, respectively. So, the dynamic hash puzzle of PoT consensus mechanism in KT-chain is shown as

$$\begin{aligned}&\mathrm{Hash}(\mathrm{ID}_{\mathrm{KAG}_i}, \mathrm{Timestamp}, \mathrm{Hash}(\mathrm{previousdata}), \mathrm{nonce})\\ &\leq \mathrm{target}_{i\_\mathrm{PoW}} \leq \mathrm{target}_{i\_\mathrm{PoT}} \quad (2)\end{aligned}$$

$$\mathrm{target}_{i\_\mathrm{PoT}} \propto KS_{i\_\mathrm{total}} = \min\left(\sum_j KS_{ij}, KS_{\max}\right) \quad (3)$$

where $\text{target}_{i\_\text{PoT}}$ and KS_{i_total} (stake) has positive correlation, and $\text{target}_{i\_\text{PoW}}$ is always smaller than $\text{target}_{i\_\text{PoT}}$. If and only if there is no stake ($KS_{i\_\text{total}} = 0$), $\text{target}_{i\_\text{PoW}}$ will be equal to $\text{target}_{i\_\text{PoT}}$. $KS_{\max}$ is set to prevent excessive stakes go beyond the range of hash function (SHA-256). The N_{i_stake} and $\text{target}_{i\_\text{PoT}}$ can be calculated through the following equations:

$$N_{i\_\text{stake}} = \text{int}(\alpha \times \ln(\beta \times KS_{i\_\text{total}}+1)) \geq 0 \quad (4)$$

$$\text{target}_{i\_\text{PoT}} = 2^{N_{i\_\text{PoT}}} - 1 = 2^{N_{i\_\text{PoW}} + N_{i\_\text{stake}}} - 1 \quad (5)$$

where α and β are fixed parameters, and int (.) function is utilized to acquire the integer part. Equation (6) clearly states the relationship among N_{i_PoW}, N_{i_stake}, N_{i_PoT}, and $N_{\max}$ about $\text{target}_{i\_\text{PoT}}$ in the proposed consensus mechanism

$$\text{target}_{i\_\text{PoT}}: \quad \underbrace{0 \quad 0 \quad 0 \quad 0 \quad \underbrace{\overbrace{1 \quad 1 \ldots}^{N_{i\_\text{stake}}} \overbrace{\ldots 1 \quad 1 \quad 1 \quad 1}^{N_{i\_\text{PoW}}}}_{N_{i\_\text{PoT}}}}_{N_{\max}=256(\text{SHA}-256)}. \quad (6)$$

Besides, according to Xu *et al.* [28], for KAG *i*, the expectation of needed computation resources of PoT mechanism is

$$\begin{aligned} E_{i\_\text{PoT}} &= \frac{\text{target}_{\max}}{\text{target}_{i\_\text{PoT}}} \times 2^{32} = \frac{\text{target}_{i\_\text{PoW}}}{\text{target}_{i\_\text{PoT}}} E_{i\_\text{PoW}} \\ &= \frac{2^{N_{i\_\text{PoW}}} - 1}{2^{N_{i\_\text{PoW}} + N_{i\_\text{stake}}} - 1} E_{i\_\text{PoW}} \approx \frac{1}{2^{N_{i\_\text{stake}}}} E_{i\_\text{PoW}}. \end{aligned} \quad (7)$$

Therefore, compared with PoW, PoT can be considered as a green mechanism with less resources consumption, whereas it could also get rid of security vulnerabilities mentioned earlier, compared with PoS. It is applicable for the edge environment. So, for our KT-chain, consensus process is based on PoT consensus mechanism rather than PoW or PoS.

V. Incentive Knowledge Pricing for Proposed Market

We assume a buyer with the total budget B will require knowledge services in the market. We first divide the total budget B into $(B_1, B_2, \ldots, B_i, \ldots, B_m)$ based on the demand proportion function $D(.)$. So, B_i shows the total budget for ith isomorphic knowledge $\Pi_i = (\pi_{i1}, \pi_{i2}, \ldots, \pi_{ij}, \ldots, \pi_{in_i})$ from n_i edge-AI knowledge sellers EAI_{ij}, $(i = 1, \ldots, m; j = 1, \ldots, n_i)$. Notice that a single edge-AI device could carry out multiple knowledge services and the number of actual sellers is less than $\sum_{i=1}^{m} n_i$. This does not conflict with the followings, each edge-AI devices can divide their resources according to service popularity and learning costs in advance [27]. The learning data size of ith knowledge from each edge-AI sellers is denoted as $\Theta_i = (\theta_{i1}, \theta_{i2}, \ldots, \theta_{ij}, \ldots, \theta_{in_i})$. The key symbols and explains are shown in Table III.

A. Knowledge Value Function

In the proposed knowledge market, we need to evaluate the value of monetized KCs. Intuitively, KCs with higher values mean higher knowledge pricing. Meanwhile, knowledge value is embodied in algorithms performances (e.g., knowledge accuracy) and the degree of satisfaction for users.

KCs are extracted via edge-AI (SVM, deep learning, and machine learning), and it is a complicated process to refine knowledge from massive raw data. In this paper, we do not pay attention to the process of knowledge refining, because this is not the focus of this paper. However, for reasonable knowledge evaluation, we need to estimate the gap between knowledge and raw data. So, we adopt two principles [29], [30] to define the knowledge value function $\psi_{\pi_{ij}}(\theta_{ij})$: first, the property of AI algorithms: the higher the data size (examples), the higher the algorithms performance (e.g., accuracy); second, the regular pattern of diminishing marginal utility: the marginal utility (performance) diminishes when the supply (data) increases. Therefore, $\psi_{\pi_{ij}}(\theta_{ij})$ should be a strictly increasing and concave function in the conditions of these two principles.

Definition 1: Knowledge value function $\psi_{\pi_{ij}}(\theta_{ij}; \eta, \gamma)$ based on abovementioned two principles is defined as follows:

$$\psi_{\pi_{ij}}(\theta_{ij}; \eta_i, \gamma_i) = 1 - \eta_i e^{-\gamma_i \cdot \theta_{ij}} \quad (8)$$

where η_i and γ_i are curve approximating parameters of $\psi_{\pi_{ij}}(\theta_{ij}; \eta_i, \gamma_i)$ to real-world data. It is an empirical function, and different types of knowledge services correspond to different parameters. According to the definition, $\psi_{\pi_{ij}}(\theta_{ij}; \eta_i, \gamma_i) \in (0, 1)$, so, it can be considered as a normalized value of knowledge. Besides, $\psi_{\pi_{ij}}(0; \eta_i, \gamma_i) = 1 - \eta_i$ indicates the lower bound of knowledge value, which means even if a small amount of learning data, the value function can guarantee least $1 - \eta_i$ knowledge value.

It is reasonable since the real-world data could be well fitted through a well-defined knowledge value/utility function, which can directly reflect the performances of the edge intelligence algorithm (e.g., accuracy). For rational users, the higher the performance of the algorithm, the higher the satisfaction rate. For instance, in [31], the authors adopted this function to show the activity recognition accuracy of artificial intelligent algorithms. The authors tested and verified the function for the classification in different machine learning algorithms, such as logistic regression and SVMs, based on an accelerometer and gyroscope samples dataset collected from waist-mounted smart phones.

B. Noncooperative Game Formulation

We suppose that n_i knowledge sellers are independently owned, so they are selfish for competing the giving budget B_i, formulating a noncooperative game. Each sellers aims to maximize their own interests. Therefore, the utility function of each sellers EAI_{ij} and the corresponding optimization problem are given as follows:

$$\begin{aligned} \max_{\theta_{ij}} U_{ij}(\theta_{ij}) &= \frac{\psi_{\pi_{ij}}(\theta_{ij}; \eta_i, \gamma_i)}{\sum_{i=1}^{n_i} \psi_{\pi_{ij}}(\theta_{ij}; \eta_i, \gamma_i)} B_i - C_{ij}\theta_{ij} \\ \text{s.t.} \quad & U_{ij\_\min}^{\text{th}} \leq U_{ij}(\theta_{ij}) \\ & \theta_{ij\_\min}^{\text{th}} \leq \theta_{ij} \leq \theta_{ij\_\max}^{\text{th}} \end{aligned} \quad (9)$$

where $U_{ij}(.)$ is the utility function of EAI_{ij}. We offer rewards based on the knowledge value provided by sellers. C_{ij} shows the distinct unit data cost of seller i for ith knowledge service, which consists of two parts: data purchase cost from IoT sensors and data learning cost in edge devices. For the first restriction, it indicates that participating sellers should obtain at least $U^{\rm th}_{ij\_\min}$. The second restriction is resulting from the resources limitation of edge-AI devices, and edge-AI devices can only process a certain range of data size, from $\theta^{\rm th}_{ij\_\min}$ to $\theta^{th}_{ij\_\max}$. Let $\Theta = (\theta_{i1}, \theta_{i2}, \ldots, \theta_{ij}, \ldots, \theta_{in_i})$ states the learning strategy space of each sellers. We need to obtain optimal learning strategy of each sellers, so we define the Nash equilibrium (NE) into the proposed model.

Definition 2: We define the learning strategy of each sellers $\Theta^* = (\theta^*_{i1}, \theta^*_{i2}, \ldots, \theta^*_{ij}, \ldots, \theta^*_{in_i})$ a NE. If $U_{ij}(\theta^*_{ij}, \Theta^*_{-ij}(\theta^*_{ij})) \geq U_{ij}(\theta_{ij}, \Theta_{-ij}(\theta_{ij}))$, where $\Theta_{-ij}(\theta_{ij})$ indicates the optimal strategies of all the other sellers except for EAI_{ij} when the strategy of EAI_{ij} is θ_{ij}.

Then, we will prove the existence and uniqueness of NE in this game. The NE guarantees that, for each seller, as long as others do not change their strategies, they cannot improve their own utilities in the NE learning strategies.

Theorem 1: There exists at least one NE learning strategy among the participating knowledge sellers in the proposed game.

Proof: According to the expression of (9), $U_{ij}(\theta_{ij})$ is continuous. We take the first-order derivative and secondary-order derivative of $U_{ij}(\theta_{ij})$ w.r.t. θ_{ij}, respectively, which are

$$\frac{\partial U_{ij}(\theta_{ij})}{\partial \theta_{ij}} = \frac{\eta_i \gamma_i e^{-\gamma_i \theta_{ij}} \cdot \Psi_{-\pi_{ij}}(\theta_{ij})}{(\Psi_{-\pi_{ij}}(\theta_{ij}) + \psi_{\pi_{ij}}(\theta_{ij}))^2} B_i - C_{ij} \tag{10}$$

$$\frac{\partial^2 U_{ij}}{\partial^2 \theta_{ij}} = \frac{-\eta_i \gamma_i^2 e^{-\gamma_i \theta_{ij}} B_i \Psi_{-\pi_{ij}}(\Psi(\theta_{ij}) + \eta_i e^{-\gamma_i \theta_{ij}})}{(\Psi_{-\pi_{ij}}(\theta_{ij}) + \psi_{\pi_{ij}}(\theta_{ij}))^4} \tag{11}$$

■

where $\Psi_{-\pi_{ij}}(\theta_{ij})$ indicates the total knowledge value provided by other sellers except for knowledge π_{ij} from EAI_{ij}. For each sellers EAI_{ij}, the strategy space is limited by lower bound $\theta^{\rm th}_{ij\_\min}$ and upper bound $\theta^{\rm th}_{ij\_\max}$. Therefore, the learning strategy Θ is a nonempty, compact, and convex subset of real number space R^n. According to (11), $\partial^2 U_{ij}(\theta_{ij})/\partial^2 \theta_{ij} < 0$. Since $U_{ij}(\theta_{ij})$ is a strictly concave function w.r.t. θ_{ij}, it is a quasi-concave function in θ_{ij}. So, the optimization problem of (9) must be a convex optimization problem. Meanwhile, at least one NE strategy among the participating knowledge sellers exists in this game.

Definition 3: Under the learning strategy $\Theta_{-ij}(\theta_{ij})$, $\Psi_{-\pi_{ij}}(\theta_{ij})$, if θ^*_{ij} maximizes the EAI_{ij} utility function $U_{ij}(\theta_{ij}, \Theta_{-ij}(\theta_{ij}))$ in (9) over the all possible value of θ^*_{ij}, the θ^*_{ij} is considered as the best response learning strategy [32].

Theorem 2: There exists a unique NE learning strategy among the participating knowledge sellers in the proposed game.

Proof: According to the definition of NE, each sellers performs the best response learning strategy when achieving the NE. We study the first-order derivative $\partial U_{ij}/\partial \theta_{ij}$ to determine the best response strategy. Since U_{ij} is a strictly concave function w.r.t. θ_{ij} $(\partial^2 U_{ij}(\theta_{ij})/\partial^2 \theta_{ij} < 0)$, $\partial U_{ij}/\partial \theta_{ij}$ is a strictly decreasing function about θ_{ij}. Then, the best response learning strategy can be calculated as follows:

$$\theta^*_{ij} = \begin{cases} \theta^{\rm th}_{ij\_\min} & U_{ij}(\theta_{ij})/\partial \theta_{ij} < 0 \\ \theta^*_{ij} & U_{ij}(\theta_{ij})/\partial \theta_{ij} = 0 \\ \theta^{\rm th}_{ij\_\max} & U_{ij}(\theta_{ij})/\partial \theta_{ij} > 0 \end{cases}. \tag{12}$$

So, we can prove that only one best response learning strategy exists in the proposed game. In other word, the uniqueness of the NE can be achieved.

C. Optimal Knowledge Pricing Strategy for Proposed Market

For the convex optimization problem (9) with restricted conditions, we introduce the Lagrangian dual function to obtain the optimal value of learning strategy θ_{ij}, which is described as

$$\begin{aligned} L_{ij}(\theta_{ij}, \chi_{ij}, \delta_{ij}, \varepsilon_{ij}) &= U_{ij}(\theta_{ij}) + \chi_{ij}(U_{ij}(\theta_{ij}) - U^{\rm th}_{ij\_\min}) \\ &\quad + \delta_{ij}(\theta_{ij} - \theta^{\rm th}_{ij\_\min}) + \varepsilon_{ij}(\theta^{\rm th}_{ij\_\max} - \theta_{ij}) \end{aligned} \tag{13}$$

where χ_{ij}, δ_{ij}, and ε_{ij} $(i = 1, \ldots, m$ and $j = 1, \ldots, n_i)$ are the adding dual variables. Given the $\Psi_{-\pi_{ij}}(\theta_{ij})$, we utilize Karush–Kuhn–Tucher (KKT) condition to derive the optimal strategy. Thus, $\partial L_{ij}(\theta_{ij})/\partial \theta_{ij} = 0$, $(\chi_{ij}, \delta_{ij}, \varepsilon_{ij} \geq 0)$. Let $[x]^+ = \max(0, x)$, we can obtain the best response learning strategy by following equations:

$$\Gamma_{ij}(\chi_{ij}, \delta_{ij}, \varepsilon_{ij}) = \frac{\gamma_i B_i \Psi_{-\pi_{ij}}(\theta_{ij})(1 + \chi_{ij})}{(\varepsilon_{ij} - \delta_{ij}) + C_{ij}(1 + \chi_{ij})} \tag{14}$$

$$\psi'_{\pi_{ij}} = \frac{-2\Psi_{-\pi_{ij}} - \Gamma_{ij} + \sqrt{\Gamma^2_{ij} + 4\Gamma_{ij}\Psi_{-\pi_{ij}} + 4\Gamma_{ij}}}{2} \tag{15}$$

$$\psi^*_{\pi_{ij}}(\theta_{ij}) = \max[1 - \eta_i, \psi'_{\pi_{ij}}(\theta_{ij})] \tag{16}$$

$$\theta^*_{ij}(\chi_{ij}, \delta_{ij}, \varepsilon_{ij}) = \psi^{-1}_{\pi_{ij}}(\theta_{ij}) = -\frac{1}{\gamma_i} \ln\left(\frac{1 - \psi^*_{\pi_{ij}}(\theta_{ij})}{\eta_i}\right) \tag{17}$$

where Γ_{ij} is an intermediate variable related to χ_{ij}, δ_{ij}, and ε_{ij}. We use the subgradient method to obtain the best learning strategy. k and λ are the iteration index and step size, respectively. The variables χ_{ij}, δ_{ij}, and ε_{ij} $(i = 1, \ldots, m$ and $j = 1, \ldots, n_i)$ are updated as follows:

$$\begin{aligned} \chi_{ij}(k+1) &= [\chi_{ij}(k) - \lambda(U_{ij} - U^{\rm th}_{ij\_\min})]^+ \\ \delta_{ij}(k+1) &= [\delta_{ij}(k) - \lambda(\theta_{ij} - \theta^{\rm th}_{ij\_\min})]^+ \\ \varepsilon_{ij}(k+1) &= [\varepsilon_{ij}(k) - \lambda(\theta^{\rm th}_{ij\_\max} - \theta_{ij})]^+. \end{aligned} \tag{18}$$

Finally, we can get the optimal value of $\psi^*_{\pi_{ij}}$ and θ^*_{ij}, so the optimal knowledge pricing strategy can be denoted as

$$P^*_{ij} = \frac{\psi^*_{\pi_{ij}}(\theta^*_{ij})}{\psi^*_{\pi_{ij}}(\theta^*_{ij}) + \Psi^*_{-\pi_{ij}}(\theta^*_{ij})} B_i \quad (i = 1, \ldots, m). \tag{19}$$

VI. Security Analysis and Performance Simulation

In this section, we first give security analysis about our knowledge market. After that, we evaluate performances about the

Algorithm 1: Optimal Knowledge Pricing Strategy Algorithm.

Input: B, $D(.)$, η_i, γ_i, C_{ij}, θ_{ij}^{th}, U_{ij}^{th}, $(i = 1, \ldots, m)$.
Output: θ_{ij}^*, P_{ij}^*, $\psi_{\pi_{ij}}^*(\theta_{ij})$, $(j = 1, \ldots, n_i)$.

Initialization: Divide total budget B into B_i by $D(.)$; initialize $\chi_{ij}(0)$, $\delta_{ij}(0)$, $\varepsilon_{ij}(0)$, $\Psi_{-\pi_{ij}}(0) \geq 0$, $k := 0$, step size λ, and precision threshold δ.
for The isomorphic knowledge from Π_1 to Π_m **do**
  for Each seller $j \in [1, n_i]$ **do**
    Calculate $\psi_{\pi_{ij}}(\theta_{ij}(k))$ according to (14)–(16).
    Calculate $\theta_{ij}(k)$ according to (17).
  end for
  Reapeat
  Each seller updates $\Psi_{-\pi_{ij}}(k+1)$ though $\psi_{\pi_{ij}}(\theta_{ij}(k))$.
  Each seller adjusts variables $\chi_{ij}(k+1)$, $\delta_{ij}(k+1)$, $\varepsilon_{ij}(k+1)$ though (18).
  for Each seller $j \in [1, n_i]$ **do**
    Calculate $\psi_{\pi_{ij}}(k+1)$ according to (14)–(16).
    $\theta_{ij}(k+1)$ according to (17).
  end for
  $k + 1 := k$.
  Until $\frac{\|\theta_{ij}^{k+1} - \theta_{ij}^{k}\|_1}{\|\theta_{ij}^{k}\|_1} \leq \delta$; $\theta_{ij}^* := \theta_{ij}^{k+1}$.
  Calculate $\psi_{\pi_{ij}}^*(\theta_{ij})$ and P_{ij}^* according to (8), (19).
end for

TABLE IV
SECURITY PERFORMANCE COMPARISON

Features	[12]	[13]	K-chain
In IoT environment	Yes	Yes	Yes
Decentralization	Yes	Yes	Yes
Nontampering	Yes	Yes	Yes
No double-spending	Yes	No	Yes
Knowledge trading	No	No	Yes
Knowledge fairness	No	No	Yes

PoT consensus mechanism and the incentive knowledge pricing strategy (IPS).

A. Security Analysis on Knowledge Market

We provide secure analysis on the knowledge market in detail in Table IV.

1) *Knowledge decentralization:* With the help of blockchain technologies, knowledge trading will get rid of the traditional third party in the market. Edge-AI entities can achieve knowledge paid sharing in a P2P manner. Blockchain-based decentralized knowledge management makes knowledge market available and reliable.
2) *Knowledge nontampering:* We assume a small portion of KAGs could be attacked and comprised by attackers in a period of time. Knowledge information and trading records stored in blockchain could be tampered by attackers. While all KAGs store a unified knowledge blockchain. Once extricating from attackers, the comprised KAGs can detect the differences from other KAGs. So, knowledge nontampering can be realized in the market.
3) *No double-spending:* Similar to *Bitcoin* system, a public history of knowledge trading will prevent double-spending in the market. The history of knowledge trading is sharing in the P2P knowledge market and is reached a consensus via PoT.
4) *Knowledge fairness:* Knowledge fairness can be guaranteed through the deployed KTSC smart contract. Only when the sellers provide the knowledge sharing for revealing encrypted knowledge, the deposits will be rewarded to sellers. If the sellers do not offer the knowledge sharing, the deposits will be aborted by KTSC. So, the nonrepudiation of knowledge trading is realized.

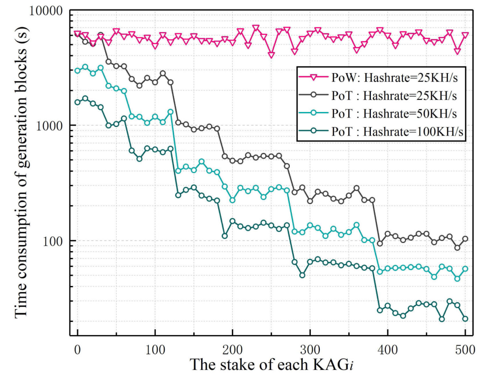

Fig. 5. Time consumption T in the PoW/PoT protocol.

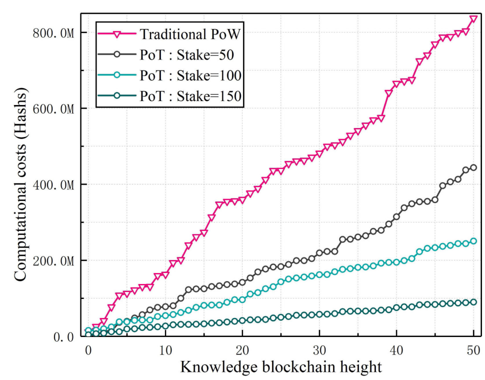

Fig. 6. Computational consumption (hash) in the PoW/PoT protocol.

B. Performance Simulation

Our performance evaluations are conducted utilizing knowledge blockchain and game theory platform based on Python and MATLAB, respectively.

In Figs. 5 and 6, we compare the performance of the proposed PoT mechanism with the traditional PoW protocol, which is widely used in the actual blockchain systems, such as *Bitcoin* [10] and *Ethereum* [11]. The periodic trading currency for each KAGs could be recorded as stakes in our market. After that, KAGs in our market attempt to act as the KT-chain miner, who has the priority of publishing the new transaction blocks. Thus,

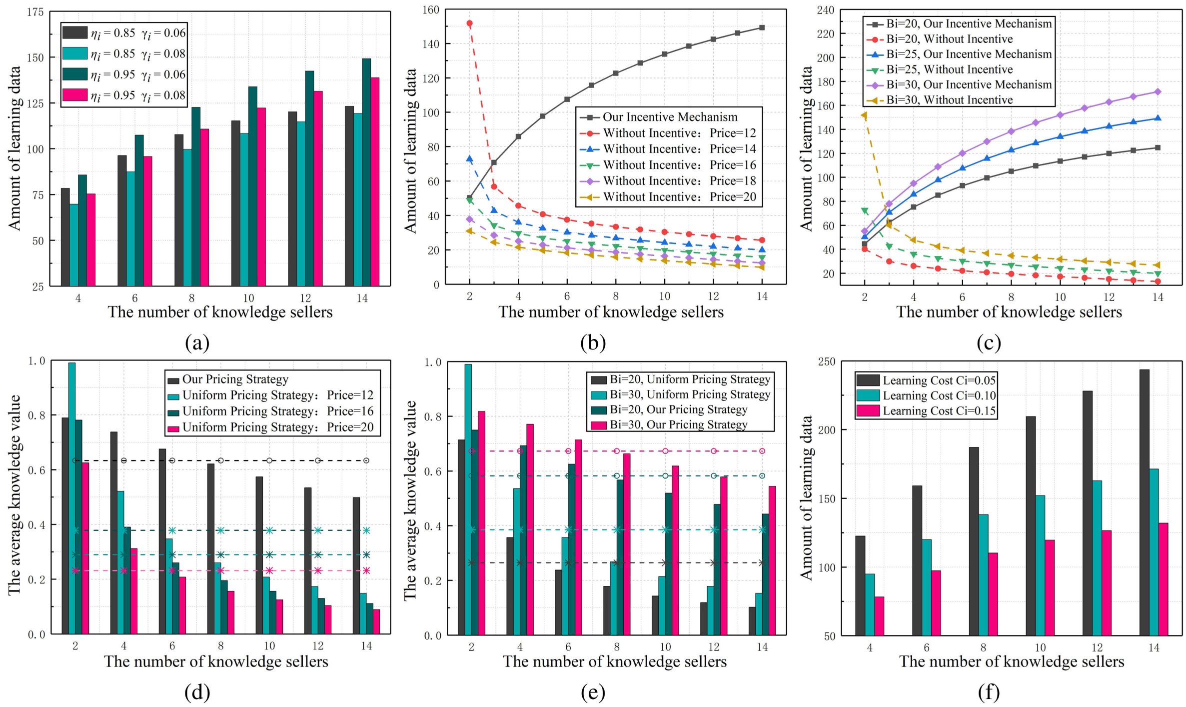

Fig. 7. Simulation results of the knowledge pricing. (a) Comparison of heterogeneous knowledge. (b) Learning data under different prices. (c) Learning data under different budgets. (d) Knowledge value under different prices. (e) Knowledge value under different budgets. (f) Influence of learning costs.

the transaction block generation time (i.e., hash puzzle solving time) T of each KAGs will be influenced by two factors: computation contribution (i.e., hash rate) and trading stakes (i.e., KS_{i_total}). Hash rate characterizes the number of hash operations per second, corresponding to the heterogeneous edge computing capacity. While trading stakes show the differentiated market contribution of each KAGs.

We find the relationship between time T, hash rate, and trading stakes in Fig. 5. The same hash algorithm SHA-256 as PoW protocol is employed in Python's hashlib library. The initial difficulty of the PoW protocol is set as $N_{i\_\mathrm{PoW}} = 232$. Besides, the block height is set to 10, which indicates the number of transaction blocks in our KT-chain. As shown in Fig. 5, for PoT protocol, time T produced by edge servers with higher hash rates will be smaller under the same stakes, which results from more hash attempts in unit time. Time T is almost proportional to the hash rate, as shown in Fig. 5. For example, when KAGs have a uniform stake 250, time T obtained by different edge computing devices with different hash rates (25, 50, and 100 kH/s) is 534.5278, 264.0129, and 134.97885 s, respectively. With the increase of stakes, time T gradually decreases under the different hash rates (25, 50, and 100 kH/s). The KAG that make more contributions to the market will have a larger stake, resulting in a larger hash puzzle threshold. This makes it easier to solve the hash puzzle, i.e., find the right conditional nonce. For comparison, we also evaluated the block generation time T based on the PoW protocol under the same computing power (hash rate $= 25$ kH/s). As shown in Fig. 5, time T fluctuates around the mean (5741.85 s) in PoW protocol with the increase of stakes. The fluctuating comes from the random characteristics of the hash algorithm. Therefore, compared with the traditional PoW protocol, the PoT protocol can show the impact of different stakes on block generation time T. Meanwhile, benefit from PoT protocol, the time T will be shortened, as shown in Fig. 5, which will shorten the time of transaction confirmation and further improve the efficiency of KT-chain.

Longer computing time means more computational and energy consumption. We utilize the accumulative hash operations to represent the consumption of computing resources. To simplify, we assume that the energy consumption per hash operation is approximately the same, thus Fig. 6 indicates both computational and energy consumption in PoW/PoT protocol. As shown in Fig. 6, the advantages of resources reduction of our PoT get more and more clear, with the increase of block height. Therefore, the proposed PoT consensus mechanism can be considered as a green consensus mechanism, which is more applicable in the edge environment.

We evaluate the performance of the proposed IPS in Fig. 7. In Fig. 7(a), we first compare the four kinds of heterogeneous knowledge with different parameters (η_i, γ_i) under the same condition (e.g., budget $B = 25$). As shown in Fig. 7(a), the higher the knowledge value lower bound $1 - \eta_i$, the less the learning data. For those kinds of knowledge with higher lower bound, they could acquire the same knowledge value according to less learning data. Also, γ_i shows the curve steepness of the knowledge value function. Higher γ_i means knowledge value changes faster as learning data increases. So, to obtain the same knowledge value, knowledge types with higher γ_i can learn less data.

Then, we show the incentive effects of our strategy IPS. Similar to [33] and [34], we compared the incentives with a uniform pricing strategy (UPS), which has no incentives. In the

UPS, for all the participating sellers, knowledge buyers give a uniform unit price p_i for knowledge value $(i = 1, \ldots, m)$. So, the knowledge value and learning strategy can be calculated as $\psi_i(\theta_{ij}) = \frac{B_i}{n_i p_i}$ and $\theta_{ij} = \psi_{ij}^{-1}(\theta_{ij})$ $(j = 1, \ldots, n_i)$. As shown in Fig. 7(b), we choose knowledge parameters ($\eta_i = 0.95$ and $\gamma_i = 0.06$), fixed budget ($B = 25$), and learning cost ($C = 0.10$), and we change the uniform price p_i from 12 to 20. When the number of sellers is small, UPS has more advantages. Because in this case, UPS will result in more learning data. However, with the increasing number of selected knowledge sellers, the amount of learning data increases in the proposed IPS. So, the proposed mechanism could be considered as an incentive mechanism in this case, which encourages sellers to learn more data under a fixed budget. In edge-AI enabled IoT, intelligent applications will depend on the cooperation among more and more edge-AI devices, due to the distributed nature of the edge environment. It means that the process of knowledge sharing will take place among more and more devices. So, IPS mechanism with incentives is more practical in real world. In Fig. 7(c), we also compare our strategy and UPS (Price = 14) under different budgets. As shown in Fig. 7(c), it indicates that incentives are also effective under the different budgets in the proposed mechanism. Moreover, in Fig. 7(d) and (e), we further demonstrate the knowledge value of KCs obtained by the two pricing strategies. As shown in Fig. 7(d), on average, the knowledge value for knowledge sellers in the proposed strategy (IPS) is 67.3%, 118.8%, and 173.4% higher than that of UPS when the price is 12, 16, and 20, respectively. Similar results can be found in Fig. 7(e). The knowledge value for knowledge sellers in the proposed scheme (UPS) is 120.1% and 74.6% higher than that of UPS under different budgets 20 and 30, respectively.

We show the influence of learning cost in Fig. 7(f) and changing cost from 0.05 to 0.15 with a fixed budget ($B = 30$). As shown in Fig. 7(f), the learning cost of sellers will directly affect learning strategy. The amount of learning data by knowledge sellers decreases with the increase of learning cost. So, for buyers, a seller with less learning cost will be a priority. This is because less learning cost for the same knowledge service will result in more learning data and higher knowledge value under the same condition.

VII. Conclusion

In this paper, to break islands of knowledge and make knowledge tradable in edge-AI enabled IoT, we proposed a P2P knowledge market for knowledge paid sharing. We utilized blockchain technologies (consortium blockchain/smart contract) to build a knowledge blockchain to ensure security and efficiency of the market. In addition, a green consensus mechanism PoT was proposed for the knowledge blockchain, which is more applicable at the edge of networks due to less resource consumption. Moreover, we proposed a noncooperative game based optimal knowledge pricing strategy as incentives for the knowledge market. We showed that the optimal pricing strategy could encourage knowledge sellers to learn more data and provide higher quality knowledge for buyers in the market. Based on the proposed knowledge market, some future works could be pursued. Knowledge extracted by machine learning could be reproduced with almost no costs. Some buyers could buy KCs from sellers, duplicate and resell knowledge to others. Thus, hierarchical market models could be introduced, e.g., Stackelberg games. Besides, the knowledge market is established upon the data/information market, so a comprehensive market and more economic models should be discussed, which take both data/information and knowledge trading into account.

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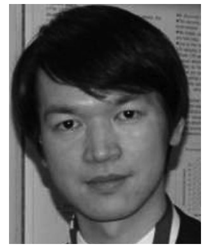
Xi Lin (S'18) received the B.S. degree in optoelectronic science and technology from the School of Precision Instrument and Optoelectronics Engineering, Tianjin University, Tianjin, China, in 2016. He is currently working toward the Ph.D. degree in cyberspace security at the School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University, Shanghai, China.

His research interests include multiaccess edge computing Internet of Things, blockchain, etc.

Jianhua Li received the B.S., M.S., and Ph.D. degrees in information security from the School of Cyber Security, Shanghai Jiao Tong University, Shanghai, China, in 1986, 1991, and 1998, respectively.

He is currently a Professor/Ph.D. Supervisor and the Dean of the School of Cyber Security, in Cyberspace security, Shanghai Jiao Tong University, and the Chairman of the Shanghai Key Laboratory of Integrated Administration Technologies for Information Security, and the Vice-Director with the National Engineering Laboratory for Information Content Analysis Technology, Shanghai. He was the Chief Expert in the Information Security Committee Experts with the National High Technology Research and Development Program of China (863 Program) and a Committee Expert with the Information Technique Standardization Committee of Shanghai, China. He was the Leader of more than 30 state/province projects of China, and authored or coauthored of more than 300 papers. His research interests include cyber security, data science, next generation networking, etc.

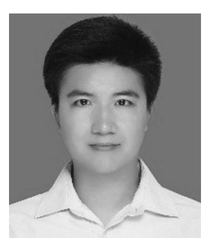
Dr. Li was the recipient of the Second Prize of the National Technology Progress Award of China in 2005 and the First Prize of the National Technology Progress Award of Shanghai in 2003 and 2004.



Jun Wu (S'09–M'12) received the Ph.D. degree in information and telecommunication studies from Waseda University, Tokyo, Japan, in 2011.

He was a Postdoctoral Researcher with the Research Institute for Secure Systems, National Institute of Advanced Industrial Science and Technology, Tokyo, Japan, from 2011 to 2012. He was a Researcher with the Global Information and Telecommunication Institute, Waseda University, from 2011 to 2013. He is currently an Associate Professor in School of Cyber Security, Shanghai Jiao Tong University with the School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University, Shanghai, China. He is also the Vice-Director of the National Engineering Laboratory for Information Content Analysis Technology, Shanghai Jiao Tong University. He is currently the Chair of the IEEE P21451-1-5 Standard Working Group. He has hosted and participated in a lot of research projects including the National Natural Science Foundation of China, National 863 Plan and 973 Plan of China, Japan Society of the Promotion of Science Projects, etc. He has authored/coauthored more than 120 refereed papers which include the advanced computing, communications and security techniques of software-defined networks, informationcentric networks smart grids, Internet of things, 5G, etc.

Dr. Wu has been the Track Chair of the Vehicular Technology Conference in 2019 and the Technical Program Committee Member of more than ten international conferences, including the International Conference on Communications, Global Communications Conference, International Wireless Internet Conference (WiNCON), etc. He has been a Guest Editor for the IEEE SENSORS JOURNAL, *Sensors*, and *ICT Express*. He is an Associate Editor for the IEEE ACCESS.



Haoran Liang received the B.S. and M.S. degrees in communication engineering from Jiangxi Normal University, Nanchang, China, in 2011 and 2017, respectively. He is currently working toward the Ph.D. degree in cyberspace security with the School of Cyber Security, Shanghai Jiao Tong University, Shanghai, China.

His current research interests include information security, blockchain, fog computing, etc.

Wu Yang received the Ph.D. degree in computer system architecture from the Computer Science and Technology School, Harbin Institute of Technology, Harbin, China, in 2005.

He is currently a Professor and a Doctoral Supervisor with Harbin Engineering University, Harbin. His main research interests include wireless sensor networks, peer-to-peer networks, and information security.

Dr. Yang is a member of the Association for Computing Machinery and a Senior Member of China Computer Federation (CCF).