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Blockchain-Based Incentive Energy-Knowledge Trading in IoT: Joint Power Transfer and AI Design

Xi Lin, Jun Wu, Ali Kashif Bashir, Jianhua Li, Wu Yang, and Md. Jalil Piran

Abstract—Recently, edge artificial intelligence techniques (e.g., federated edge learning) are emerged to unleash the potential of big data from Internet of Things (IoT). By learning knowledge on local devices, data privacy-preserving and quality of service (QoS) are guaranteed. Nevertheless, the dilemma between the limited on-device battery capacities and the high energy demands in learning is not resolved. When the on-device battery is exhausted, the edge learning process will have to be interrupted. In this paper, we propose a novel Wirelessly Powered Edge intelliGence (WPEG) framework, which aims to achieve a stable, robust, and sustainable edge intelligence by energy harvesting (EH) methods. Firstly, we build a permissioned edge blockchain to secure the peer-to-peer (P2P) energy and knowledge sharing in our framework. To maximize edge intelligence efficiency, we then investigate the wirelessly-powered multi-agent edge learning model and design the optimal edge learning strategy. Moreover, by constructing a two-stage Stackelberg game, the underlying energy-knowledge trading incentive mechanisms are also proposed with the optimal economic incentives and power transmission strategies. Finally, simulation results show that our incentive strategies could optimize the utilities of both parties compared with classic schemes, and our optimal learning design could realize the optimal learning efficiency.

Index Terms—Edge intelligence, wireless power transfer, permissioned blockchain, incentive mechanism, game theory.

I. Introduction

The emerging artificial intelligence (AI) technology (e.g., machine learning) is a promising way to cope with the data explosion of IoT applications. The knowledge that AI learns from IoT data could bring many benefits to the QoS of IoT users [1]. However, the traditional cloud-centric learning paradigm faces many challenges, such as high maintenance costs, data privacy risk, and high service delay. According to [2], over 6 billion smartphones and 50 billion IoT devices will appear by 2020 with abundant under-utilized computing, communication, and storage resources. These large-scale smart devices could address cloud-centric learning challenges. Thus, on-device federated edge learning (FEL) paradigm was proposed by Google in 2016 [3]. It employs smart edge devices to perform model training in a distributed and collaborative

manner, also known as "edge intelligence" or "edge AI" [4]. Only local sub-models (knowledge) rather than raw data will be uploaded and aggregated in FEL, which ensures local data privacy-preserving and better resource utilization [5] [6].

On-device FEL has many advantages over cloud-centric learning, but the learning performance is likely compromised by insufficient battery energy in traditional battery-powered edge devices, such as mobile phones, UAV (Unmanned Aerial Vehicle), and IoT devices. On the one hand, the local model training will consume limited battery power for the CPU cycles. On the other hand, edge devices are required to repeatedly communicate with the sink node (e.g., base station) to iteratively update the learning model, which also places severe demands on the battery level. Most previous works [7] [8] assume that the battery power of edge devices is sufficient to support the whole learning process, while this is not feasible in many practical scenarios. In fact, the on-device FEL process will be interrupted and smart edge devices cannot execute learning services if the battery is exhausted. So, the current edge intelligence framework is not stable and robust enough.

To prolong the battery life of smart devices, common method resorts to computation offloading to MEC (Mobile Edge Computing) nodes or other D2D (Device-to-Device) enabled devices [9] [10]. However, this method goes against the privacy-preserving feature of FEL. That is, this method could not apply to on-device FEL due to the privacy risks in learning task offloading. Another straightforward method is to employ larger batteries or recharging the batteries frequently. On one hand, increasing the battery capacity of each smart device is unrealistic, which will raise too much hardware cost for smart device manufacturers and owners. On the other hand, recharging device batteries frequently shows one of the most unfavorable features of smart devices and it is also impossible in certain situations, such as surveillance intelligent IoT nodes, where the devices are usually difficult to reach. Besides, to achieve green communication and computing in 5G and beyond networks, novel energy supply models need further research. The emerging energy harvesting (EH) techniques have the potential to address the above issues well. The renewable energy from the surrounding environment could be captured, harvested, and stored (e.g., solar, wind, thermal, and electromagnetic). Benefit from EH techniques, energy-saving and sustainable computing and communication applications could be realized. Thus, by the marriage of EH techniques and edge intelligence, satisfied and sustained on-device learning performance is guaranteed.

Wireless power transfer (WPT) is one of the most promising EH techniques, which employs radio frequency (RF) to offer

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controllable energy supply for smart devices [11]. Compared with other techniques, WPT has higher availability, stability, and controllability. For wirelessly-powered smart devices, the received RF signal could be easily converted into stable direct current to power the batteries of smart devices. In this paper, we propose a novel Wirelessly Powered Edge intelliGence framework (WPEG), which integrates WPT to battery-constrained on-device learning. WPT brings new possibilities to edge intelligence, while still introduces some new challenges. 1) Distributed wireless power transfer is hard to guarantee security due to some selfish and untrusted behaviors (e.g., free-rider or cheating). 2) WPT improves the energy efficiency of smart devices, while consumes higher energy in the absence of an optimal charging policy. 3) WPT nodes could not actively provide charging services without some suitable monetization incentives. To resolve the above challenges, in this paper, we also employ a pemissioned blockchain approach to establish a secure P2P (Peer-to-Peer) energy trading for edge intelligence. Moreover, a two-stage Stackelberg game model is proposed to obtain the optimal transmission power strategies and incentive strategies. The contributions of our work are summarized as follows:

- We propose a novel wirelessly-powered edge intelligence framework (WPEG) to ensure the learning performance of edge intelligence in a secure and energy-saving manner.
- We establish a pemissioned edge blockchain with a lightweight consensus protocol BFT-DPoS to secure the P2P energy and knowledge sharing.
- We build the wirelessly-powered multi-agent edge learning model, including the energy-aware computing and communication model.
- We design a Stackelberg game model to simulate the energy-knowledge trading process and derive the optimal power strategies and economic incentive strategies.

The remainder of this paper is structured as follows. Section II gives an overview of the related works. Section III describes our WPEG framework, including the framework implementation and edge permissioned blockchain. In Section IV, we present the system model of our WPEG framework. Section V formulate and analyse the proposed Stackelberg game for energy-knowledge trading. In Section V, we conduct simulations to show the advanced performance of our framework. Finally, Section VII concludes this paper.

II. RELATED WORK

A. Wireless Power Transfer in IoT

Wireless power transfer (WPT) techniques employ radio frequency (RF) signals as a promising power supplying for energy-constrained IoT devices. Some researches focus on the feasibility of applying the WPT solutions to conventional communication systems. In [12], Lee *et al.* proposed a new WIPE protocol, which realizes sustainable communications between two devices by wireless power splitting. And a joint data-energy beamforming and SWIPT-based traffic offloading scheme [13] has been proposed for C-RANs via D2D communications. Besides, a channel coding-based IoT communication network with WPT stabilization algorithms has been presented in [14]. Some other works introduced WPT technologies into mobile edge computing (MEC) systems. In [15], the authors studied a multi-user MEC system with WPT functions, and jointly optimized the computation offloading and transmission time allocation in the system. And an energy-effective cooperative resource allocation policy for the WPT-MEC system was also proposed in [16] to guarantee the fairness of mobile users. In addition, Liu *et al.* in [17] presented a UAV-assisted WPT-MEC system, and studied the joint optimization of task offloading, CPU control, and trajectory design. There are still some existing works considering cache-aided WPT-IoT networks. In [18], Gautam *et al.* investigated the relay selection strategy in a cache-aided SWIPT framework with a dynamic time switching (TS). And a sleeping mechanism for cache-aided heterogeneous networks with energy harvesting methods has been presented in [19].

In general, wirelessly-powered IoT networks have been well studied, but are limited to wirelessly-powered communication, computing, and caching in IoT networks. Although the combination of WPT technologies with the emerging edge AI technologies could improve the edge learning performance in IoT, which is ignored by the previous works.

B. Edge Intelligence for IoT

Combined with edge computing, the emerging edge AI has already become the last mile of artificial intelligence for IoT [20] [21]. Once appeared, it received a tremendous amount of interest. In terms of edge AI algorithms, in [22] [23], Li *et al.* proposed an Edgent framework, which leverages device-edge synergy computing to accelerate training and inference of deep neural network (DNN). And the authors in [24] design a momentum federated learning (MFL) framework to accelerate federated learning by momentum gradient descent. In addition, a sparse ternary compression (STC) framework [25] was designed for federated learning with non-i.i.d data. Moreover, in [26], Zhou *et al.* employed the Lyapunov optimization theory to design an online cost-efficient federated learning optimization framework named CEFL under the dynamic training data arrive. For resource sharing in edge AI, an efficient and incentive knowledge market was proposed in [27], which achieves secure and efficient edge knowledge sharing and exchange for edge AI. In [28] [29], the authors proposed a privacy-preserved data sharing scheme in industrial IoT (IIoT). In [30], a secure and robust federated learning scheme with differential privacy has been proposed for urban informatics.

Some existing works [7] [8] assumed the energy of edge devices could support the computing-intensive learning task, which is not realistic. Others [31] [32] adopted the energy as a constraint condition for task execution, which results in limitations in learning performance. Compared with existing works, our WPEG framework not only could achieve a stable, robust, and sustainable edge learning, but also improve the efficiency and performance of edge AI.

C. Blockchain for IoT

Blockchain is a feasible tool to establish distributed trust among IoT devices. In [33], Yang *et al.* proposed a blockchain-
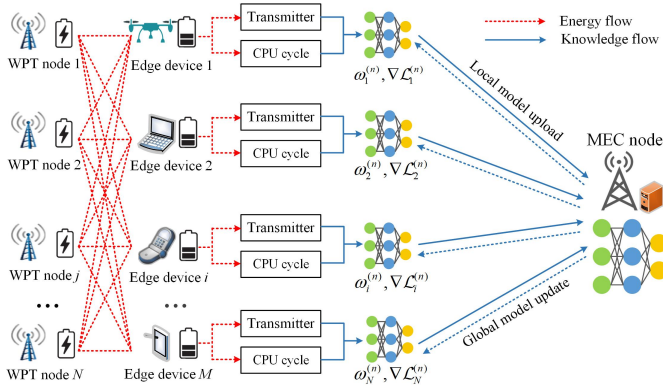
Fig. 1: The framework of our proposed WPEG.

based decentralized trust management system in vehicular networks. And a blockchain-based trustworthy computing resource trading system in vehicular networks has been discussed in [34]. For IIoT, Li *et al.* [35] built a consortium energy blockchain with a credit-based payment scheme to realize fast and frequent energy trading. And Zhang *et al.* [29] designed an edge-AI and blockchain enabled IIoT framework, which supports flexible and secure edge service management. In terms of data security, Xu *et al.* [36] proposed a novel blockchain-based trustworthy edge caching scheme for cyber-physical systems (CPSs). And the authors in [28] incorporated differential privacy into permissioned blockchain for privacy-preserved data sharing in IIoT. Some other works focus on blockchain-based incentive mechanisms, a consortium blockchain-based efficient and incentive Approach for IoT knowledge sharing has been presented in [27]. And the authors in [37] investigated the incentive mechanism for rational miners in edge-computing-enable blockchain systems. Moreover, a Stackelberg game-based incentive computing resource management has been studied in [38] for proof-of-work (PoW) based public blockchain networks.

Some previous works mainly focused on classic blockchain consensus protocols (such as PoW [37] [38]), while lightweight consensus protocols for edge blockchain systems (such as DPoS) have not been well applied. Besides, previous works only considered a single type of resource sharing (such as knowledge [27] or energy [35]), while multi-resource sharing did not involve.

III. Wirelessly-Powered Edge Intelligence Framework

We propose the novel WPEG framework in this section. First, we introduce the main elements of the WPEG framework and show how they interact in detail. Then, we provide the details of the proposed permissioned edge blockchain in our WPEG framework.

A. The Elements in Our WPEG Framework

We consider our WPEG framework is deployed at the edge of networks, which includes geo-distributed MEC (Mobile Edge Computing) nodes, large-scale edge devices and WPT

(Wireless Power Transfer) nodes, as shown in Fig. 1. Each upstream MEC node is responsible for managing edge devices and WPT nodes within its coverage. The WPEG framework mainly contains the following elements.

- **WPT nodes:** We deploy a certain number of wireless charging stations as infrastructure in the edge network environment. These WPT nodes could not only obtain energy from the traditional power grid, but also have the ability to harvest renewable energy from the surrounding environment (e.g., solar and wind) with EH equipment. The energy stored in WPT nodes will charge edge devices via wireless channels. We consider two possible transmission paths: 1) Stationary mode: when edge devices are close to the static power beacon, then it will start to emit radio waves to supplement energy; 2) Dynamic mode: the power beacon is deployed on mobile objects (e.g., drones and vehicles) and charges edge devices in a dynamic manner. Our WPEG framework implementation could employ one or two of the above models for supplement wireless energy to edge devices.

- **Edge devices:** Edge devices, such as smart phones, UAVs, IoT intelligent sensors, and microservers (Raspberry Pi), are required to provide edge AI services (i.e., federated edge learning) through local data training. Edge devices are energy-constrained so that they are difficult to guarantee a stable and robust learning performance. Thus they will obtain the wireless energy from WPT nodes. On the one hand, they utilize the wireless energy for executing model training (CPU cycle); On the other hand, they employ the wireless energy to repeatedly communicate (transmitter) with the upper MEC node for global learning model updating.

- **MEC nodes:** The MEC node first serves as the mediation between the edge AI service requester and edge devices. That is, the service requester will publish tasks, design optimal learning strategy, and reward the contribution of edge learning through MEC nodes. Besides, the local MEC node plays the role of aggregator in federated edge learning, which is responsible for collecting, aggregating, and updating the trained local sub-models from edge devices. Moreover, in order to ensure the security features of the entire framework, an edge permissioned blockchain will be established between MEC nodes to guarantee the secure P2P wireless energy sharing and knowledge (model) sharing.

In Fig. 2, we show that how the elements interact with each other, and also present how our WPEG framework works. As shown in Fig. 2, the interactive process is divided into 5 steps:

- **Step 1:** Edge AI service requesters will publish edge learning tasks through MEC nodes, and set corresponding learning parameters (e.g., local/global training accuracy) and service time limits. Then the MEC node will select the corresponding edge devices to perform the learning task according to the service type and resource status of the local edge devices.
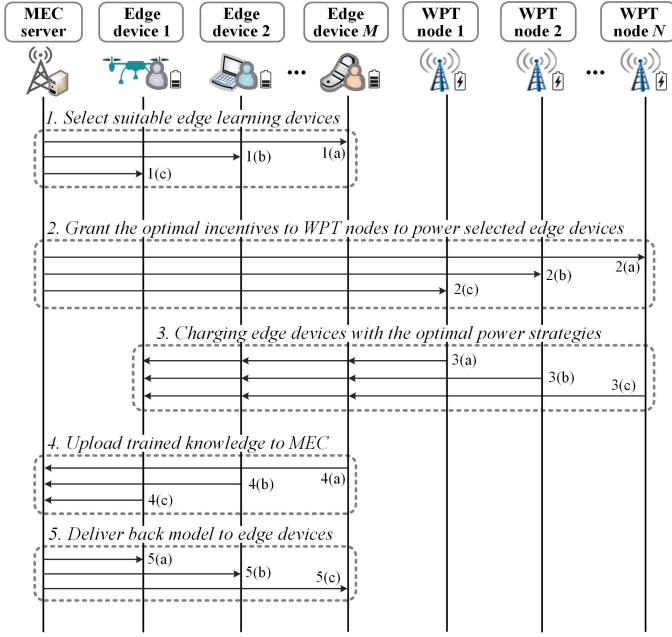
Fig. 2: The interaction of elements in our WPEG framework.

- **Step 2:** Due to the limited energy of edge devices, it is difficult to complete the whole learning task. In order to obtain training model (knowledge) from edge devices, the edge AI service requester needs to incentivize local WPT nodes to power edge devices, so that edge device can ensure the stable and robust learning process. We believe that WPT nodes are selfish and will not provide charging services for free. Thus this process requires edge AI service requesters to provide appropriate economic incentives for WPT owners through the MEC node. The details about economic incentives are given in Section V.

- **Step 3:** WPT nodes will charge edge devices under the economic incentives. In order to avoid wasting energy during this process, it is necessary to obtain the optimal power transmission strategy according to energy demands in the edge learning process. At the same time, it also needs to solve the security problems in P2P wireless energy sharing (e.g., free riding). The details about optimal power transmission strategy are given in Section V.

- **Step 4 and Step 5:** Under the predetermined time limit and learning accuracy requirements, edge devices will adopt the received energy from WPT nodes to implement federal edge learning, and upload the trained sub-models (knowledge) to the MEC server for aggregation. Then the MEC node will update the global model and deliver it back to all the edge devices. **Step 4** and **Step 5** are performed in a periodic manner. Eventually, the MEC node feeds the trained global model back to the edge AI service requester.

It should be noted that the service requesters also need to give corresponding rewards to edge devices, which can be considered as knowledge service trading. The corresponding reward mainly depends on the data contribution of edge devices in the learning process, which has been discussed in our previous works [27]. In the following text, we believe that edge devices have already decided the optimal data contribution d_i^*, and the service requester has designed the optimal knowledge service pricing strategy.

B. Permissioned Blockchain in Our WPEG Framework

As shown in Fig. 3, there are two trading modes in our framework, i.e., wireless energy trading and knowledge service trading. And the process of both energy and knowledge sharing will carry out in a Peer-to-Peer (P2P) manner. We believe that all parties in the trading process are untrusted individuals. Thus our framework will face many security attacks. For example, the free-rider, greedy and cheating energy (or knowledge) sharing phenomenon will happen in our framework. That is, on the one hand, some untrusted edge devices will deny the reception of wireless energy, which will cause great energy consumption of WPT nodes; on the other hand, the service requester may deny the acquired knowledge services, which damages the profit of edge devices. Besides, the traditional centralized trading management system also faces the single point of failure, distributed denial of service (DDoS) and Sybil attacks, which will greatly affect the security and system efficiency of our framework.

The emerging blockchain technology has become a promising distributed solution for implementing secure P2P trading. It does not rely on any centralized entity and has gained wide attention from academia and industry for its anonymity, security, and traceability. Motivated by this, we adopt blockchain technologies to defend against the security threats in our framework. Specifically, we build an edge permissioned (consortium) blockchain as a distributed energy/knowledge trading management platform, which could also encourage both parties to participate in our framework under a security guarantee. Unlike the previous work [35] [39], we employ a more lightweight and efficient consensus protocol BFT-DPoS (Byzantine Fault Tolerance-Delegated Proof of Stake) in resource-constrained edge environment, which is popular in *EOS* project. The proposed edge permissioned blockchain based on the BFT-DPoS consensus protocol works as the following phases:

Phase 1. *Market initialization:* Each entity (e.g., edge devices, WPT nodes, and MEC nodes) will first be authorized by TA (Trust Authority) to becomes a legitimate participant in the trading market. That is, TA will verify the service capabilities of each entity, and only entities that meet the service requirements can join our market. Besides, each authorized entity i will obtain corresponding asymmetric keys $\{PK_i^k, SK_i^k\}$ and certificates $\{Cert_i^k\}$ from TA. Moreover, each participant will have a wallet account $\{Wallet_i^k\}$ to manage their cryptocurrency.

Phase 2. *Miner group formation:* The local MEC node is responsible for recording and managing local transaction data as shown in Fig. 3. And MEC nodes also act as miners of the blockchain to complete the consensus process. The MEC node applies for being a miner by submitting a deposit (stakes) to the blockchain system. If the MEC node performs malicious operations in the subsequent consensus process, this deposit will be cleared.
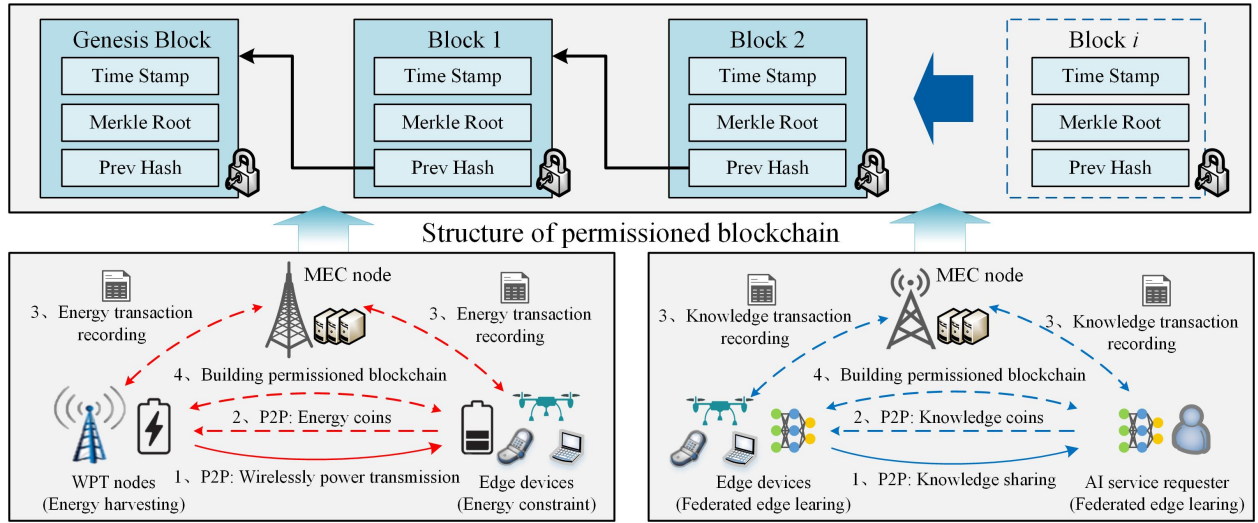
Fig. 3: The permissioned blockchain in our proposed WPEG.

Phase 3. *Delegated miner selection:* Each other entity (i.e., WPT nodes and edge devices) has its own stakes, thus they could vote for the miners and select their delegates. The top-k miners of the miner group with high stakes could be selected as the delegates of our blockchain , where k is an odd integer (e.g., $k = 21$ in *EOS* project). These delegates are responsible for the generation, management and mutual verification of transaction blocks in our blockchain. And the selection of delegates will be conducted in a periodic manner.

Phase 4. *BFT consensus process:* In order to clearly illustrate the consensus process, we still take the *EOS* project as an example. In the traditional DPoS consensus process, a delegate is randomly selected as the leader to generate a transaction block. We assume the block generation time is 3 seconds in *EOS* project, thus it will take 45 seconds to confirm the transaction in this block. Because the transaction confirmation requires more than 2/3 delegates (i.e., 14 delegates) to verify. Only when other delegates generate new blocks, the confirmation of the entire previous blockchain is completed. So it will take 45 seconds to confirm the transaction in the DPoS protocol. To further improve performance, we introduced the BFT mechanism in the consensus process. The selected leader still broadcasts the new block, but other delegates immediately verify the block after receiving this block, and return the results with the verified signature to the leader. From the perspective of the current leader, it produces a new block and broadcast it to the whole network, and then received confirmation from other delegates. If 2/3 delegates have the consistent results. The transaction in this block is irreversible. The transaction confirmation time is greatly shortened, from 45 seconds to about 3 seconds. After all the delegates complete the block consensus process, the blockchain system will give corresponding cryptocurrency rewards to their wallet.

The energy/knowledge trading is shown in Fig. 3, which is presented as follows: energy/knowledge traders first obtain $\{PK_i^k, SK_i^k\}$, $\{Cert_i^k\}$, and $\{Wallet_i^k\}$ via market initialization. Authorized traders with legal certificates can access the local MEC transaction server to initiate a transaction.

The local MEC server could match the supply and demand side of the resource. After wirelessly power transfer (or knowledge sharing), the energy/knowledge buyer needs to pay for corresponding rewards (i.e., energy coins or knowledge coins). Specifically, a new transaction will be generated by traders and recorded by the local MEC server for audit. All the MEC servers will establish a permissioned edge blockchain for cross-auditing and mutual verification, which adopts the lightweight BFT-DPoS protocol for cross-domain consensus.

IV. SYSTEM MODEL

In this section, we model the wirelessly-powered multi-agent learning process and formulate the utility function of both parties. In our proposed WPEG framework, we consider there exists M edge devices and N WPT nodes, which are represented as $\mathcal{M} = \{1, 2, ..., i, ..., M\}$ and $\mathcal{N} = \{1, 2, ..., j, ..., N\}$. All the edge devices are equipped with EH components and completely powered by the collected wireless energy from WPT nodes. Federated learning mainly contains two parts: local training and global updating. For each local training, it can be subdivided into the computing (training) process and the communication (uploading) process.

A. Preliminaries of Federated Learning

In federated learning, each edge device i ($\forall i \in \mathcal{M}$) owns a local personal dataset $\mathcal{D}_i$. And the size of data samples in $\mathcal{D}_i$ is denoted as d_i. Each data sample contains an input-output pair $\{\boldsymbol{x}_k, \boldsymbol{y}_k\}_{k=1}^{d_i}$, where the input $\boldsymbol{x}_k$ is a sample vector with various features, and the output $\boldsymbol{y}_k$ is the label value of the input features from users' mobile application. The loss function of federated learning is defined as $f_k(\boldsymbol{x}_k, \boldsymbol{y}_k, \boldsymbol{\omega})$. Some example loss functions are $f_k(\boldsymbol{x}_k, \boldsymbol{y}_k, \boldsymbol{\omega}) = 0.5\|\boldsymbol{y}_k - \boldsymbol{\omega}^T \boldsymbol{x}_k\|^2$ for linear regression and $f_k(\boldsymbol{x}_k, \boldsymbol{y}_k, \boldsymbol{\omega}) = 0.5\lambda\|\boldsymbol{\omega}\|^2 + 0.5 \max\{0; 1 - \boldsymbol{y}_k \boldsymbol{\omega}^T \boldsymbol{x}_k\}^2$ for squared-SVM. For each edge device with dataset $\mathcal{D}_i$, the local average loss function is

$$\mathcal{L}_i(\boldsymbol{\omega}) = \frac{1}{|\mathcal{D}_i|} \sum\nolimits_{k=1}^{k=d_i} f_k(\boldsymbol{x}_k, \boldsymbol{y}_k, \boldsymbol{\omega}) \tag{1}$$

Thus, the loss function minimization problem of global learning process could be described as follows:

$$\min_{\boldsymbol{\omega}^*} \mathcal{L}_{gobal}(\boldsymbol{\omega}) = \frac{|\mathcal{D}_i| \sum_{i \in \mathcal{M}} \mathcal{L}_i(\boldsymbol{\omega})}{\sum_{i \in \mathcal{M}} |\mathcal{D}_i|} \qquad (2)$$

1) Local training: Each edge device i solves the local loss function minimization problem with a local accuracy δ_i ($0 \leq \delta_i \leq 1$) as follows:

$$\boldsymbol{\omega}_i^{(n)} = \arg \min \mathcal{L}_i(\boldsymbol{\omega}_i | \boldsymbol{\omega}_i^{(n-1)}, \nabla \mathcal{L}^{(n-1)}(\boldsymbol{\omega}_i)) \qquad (3)$$

Where $||\nabla \mathcal{L}_i(\boldsymbol{\omega}_i^{(n)})|| \leq \delta_i ||\nabla \mathcal{L}_i(\boldsymbol{\omega}_i^{(n-1)})||$ at the nth model update. When $\delta_i = 0$, it shows the local problem has been solved optimally, while $\delta_i = 1$ means no progress at all in the local training [5] [40]. Each edge device then uploads weights $\boldsymbol{\omega}_i^{(n)}$ and gradients $\nabla \mathcal{L}_i^{(n)}$ to the MEC node for aggregating the global model.

2) Global updating: The MEC node collects and aggregates the uploading sub-models from edge devices as:

$$\boldsymbol{\omega}^{(n+1)} = \frac{1}{M} \sum_{i \in \mathcal{M}} \boldsymbol{\omega}_i^{(n)}, \nabla \mathcal{L}^{(n+1)} = \frac{1}{M} \sum_{i \in \mathcal{M}} \nabla \mathcal{L}_i^{(n)} \qquad (4)$$

Then the MEC node will send the global model back to all the edge devices. The interactive learning process will be carried out in an iterative manner. Until $||\nabla \mathcal{L}(\boldsymbol{\omega}^{(n)})|| \leq \alpha ||\nabla \mathcal{L}(\boldsymbol{\omega}^{(n-1)})||$ is realized, the global iteration will stop. Where $\alpha \in [0, 1]$ represents the global model accuracy. Due to the convex objective $\mathcal{L}_i$ and $\mathcal{L}_{global}$, the local iterations is general upper bounded to $\mathcal{O}(\log(1/\delta_i))$, which is applicable for a wide range of iterative algorithms (e.g., gradient or stochastic descent) [5] [40]. Besides, the global iterations could be calculated as $\mathcal{O}(\log(1/\alpha))/(1 - \delta_i)$, which is very intuitive. When global accuracy α is bigger (lower accuracy), the federated learning systems need to runs less global iterations. And when local accuracy δ_i is bigger (lower accuracy), the federated learning systems need to runs more global iterations.

B. Wirelessly-Powered Computing Model for Learning

In our WPEG, we assume each WPT node j ($j \in \mathcal{N}$) will provide controllable and constant RF energy transfers for each edge device i ($i \in \mathcal{M}$). And the transmission power is shown as $\boldsymbol{\theta} = (\theta_1, \theta_2, ..., \theta_j, ..., \theta_N)$. We believe that the MEC node could schedule spectrum resources well, i.e., the RF energy transmission and sub-models uploading will work in different frequency bands, thus the signal interference by edge devices could be ignored. The amount of energy harvested by edge devices only depends on the transmission power $\boldsymbol{\theta}$ and the channel power gain h_{ji} ($\forall j \in \mathcal{N}, i \in \mathcal{M}$). We employ a typical linear energy harvesting model like previous works [41]. Therefore, the harvested energy by edge device i from WPT nodes could be shown as:

$$E = \kappa_i T \sum_{j \in N} h_{ji} \theta_j = \Theta_i T, \ \forall i \in \mathcal{M} \qquad (5)$$

Where E and T represents energy consumption and transmission time, respectively. And $\kappa_i \in [0, 1]$ shows the energy harvesting efficiency.

We assume each edge device i will contribute the CPU computing resource $f_i \in [0, f_i^{\max}]$ in the local training process. And the number of CPU cycles for edge device i to train one sample of local data is c_i. Thus, the local computing time T_i^{cmp} is equal to $\mathcal{O}(\log(1/\delta_i))c_i d_i / f_i$. And the energy consumption of local training E_i^{cmp} is equal to $\mathcal{O}(\log(1/\delta_i))\mu_i c_i d_i f_i^2$, where the μ_i is the effective capacitance coefficient of edge device i. We consider that all the computing energy will be supplied by the RF energy from WPT nodes, thus we can get:

$$E_i^{cmp}(f_i) = \Theta_i T_i^{cmp}(f_i), \ \forall i \in \mathcal{M} \qquad (6)$$

By substitute T_i^{cmp} and E_i^{cmp} into Eq. (6), we could obtain the computing resource scheduling strategy f_i as:

$$f_i(\Theta_i) = \min[\sqrt[3]{\frac{\kappa_i}{\mu_i} \sum_{j \in \mathcal{N}} h_{ji} \theta_j}, f_i^{\max}], \ \forall i \in \mathcal{M} \qquad (7)$$

That is, in the EH-enable training process, edge devices need to adjust own computing resources to meet the energy constraints. It can be achieved by changing the voltage of computing chipset with DVFS (Dynamic Voltage and Frequency Scaling) techniques. Moreover, we could derive the T_i^{cmp} and E_i^{cmp} in local training process as follow:

$$T_i^{cmp}(\Theta_i) = \mathcal{O}(\log(\frac{1}{\delta_i}))c_i d_i \sqrt[3]{\frac{\mu_i}{\kappa_i \sum_{j \in \mathcal{N}} h_{ji} \theta_j}} \qquad (8)$$

$$E_i^{cmp}(\Theta_i) = \mathcal{O}(\log(\frac{1}{\delta_i}))c_i d_i \sqrt[3]{\mu_i \kappa_i^2 (\sum_{j \in \mathcal{N}} h_{ji} \theta_j)^2} \qquad (9)$$

C. Wirelessly-Powered Communication Model for Learning

After completing the local training, each edge device then uploads sub-models to the MEC node via the wireless uplink. Similarly, the required energy for communication is completely provided by the RF energy. Based on Eq. (5), the uplink transmit power of edge device i is $P_i = E_i^{com}/T_i^{com} = \Theta_i$. Thus the data rate (bit/s) of edge device i is shown as:

$$r_i = B \log_2(1 + \frac{P_i H_i}{N_0 B}) = B \log_2(1 + \frac{\kappa_i H_i}{N_0 B} \sum_{j \in \mathcal{N}} h_{ji} \theta_j) \qquad (10)$$

Where B represents the bandwidth, H_i shows the wireless channel gain between edge device i and the MEC node, and N_0 denotes the noise power spectrum density.

We assume the data size of both local weights $\boldsymbol{\omega}_i^{(n)}$ and local gradients $\nabla \mathcal{L}_i^{(n)}$ is ρ_i. Thus the communication time T_i^{com} and communication energy consumption E_i^{com} could be described as follows:

$$T_i^{com} = \rho_i / r_i = \frac{\rho_i}{B \log_2(1 + \frac{\kappa_i H_i}{N_0 B} \sum_{j \in \mathcal{N}} h_{ji} \theta_j)} \qquad (11)$$

$$E_i^{com} = P_i T_i^{com} = \frac{\rho_i \kappa_i \sum_{j \in \mathcal{N}} h_{ji} \theta_j}{B \log_2(1 + \frac{\kappa_i H_i}{N_0 B} \sum_{j \in \mathcal{N}} h_{ji} \theta_j)} \qquad (12)$$

It should be noted that when the global model is fed back from the MEC node to edge devices, we ignore the downlink communication time and energy consumption. This is because the downlink rate from the MEC node to edge devices is higher

TABLE I: Main Terms Referred in Our Framework

Symbol	Explanations
$\mathcal{M}$	Edge device set to execute learning tasks
$\mathcal{N}$	WPT node set to charge edge devices
c_i	The CPU cycles number required for one sample data training for edge device i
d_i	The data size of local personal dataset of edge device i
δ_i	The local sub-model trained accuracy of edge device i
h_{ji}	The channel power gain between WPT node j and edge device i
a_j, b_j, e_j	The energy cost factors of the WPT node j.
θ_j	The transmission power of the WPT node j
R_j	The economic reward for the WPT node j
T_i^{com}	The communication time of edge device i
T_i^{cmp}	The computing time of edge device i
E_i^{com}	The energy consumption of edge device i in communication process
E_i^{cmp}	The energy consumption of device i in computing process
U^{MEC}	The utility function of the MEC node
U_j^{WPT}	The utility function of the WPT node j

than uplink rate from edge devices to BS. Meanwhile, the MEC node is not subject to energy restrictions.

D. Utility Function Formulation

In our WPEG, we consider that WPT nodes are conditional volunteers. That is, power transmission can only be carried out if the corresponding economic incentives are obtained. We assume service requesters will publish federated learning tasks through the MEC node, and give WPT nodes economic rewards. The rewards for unit power transmission of WPT nodes are defined as $\boldsymbol{R} = (R_1, R_2, ..., R_j, ..., R_N)$. Thus, we could formulate the utility function of WPT nodes and the MEC node (service requesters). The main symbols and explanations in WPEG framework are shown in **TABLE 1**.

1) Utility function of WPT nodes: On the one hand, WPT nodes could obtain rewards from the MEC node, on the other hand, they still need to pay the corresponding energy costs to the energy supplier. In our paper, we employ the typical quadratic function model to represent the energy cost of WPT nodes [42]. Therefore, the utility function of WPT nodes is described as follows:

$$U_j^{WPT}(R_j, \theta_j) = R_j\theta_j - (a_j\theta_j^2 + b_j\theta_j + e_j), \forall j \in \mathcal{N} \quad (13)$$

Where a_j, b_j, e_j are the energy cost factors of the WPT node j ($\forall j \in \mathcal{N}$). Besides, a_j, b_j are positive constants for each WPT node j, and $e_j = 0$.

2) Utility function of the MEC node: In order to obtain a trained AI model (i.e., knowledge) from edge devices, the MEC node needs to give economic incentives to WPT nodes for charging. While the profit of the MEC node lies in the

quality of the local AI training service. We assume that the MEC node will pre-set a deadline $T_i^{\max}$ for completing AI training sub-tasks for each edge device i. The quality of the local AI training service of edge device i could be defined as:

$$\varphi_i(\Theta_i) = T_i^{\max} - T_i^{learn}(\Theta_i), \ \forall i \in \mathcal{M} \quad (14)$$

Where $T_i^{learn}(\Theta_i) = T_i^{cmp}(\Theta_i) + T_i^{com}(\Theta_i)$ represents the total time for local training. Besides, to realize the proportional fairness among edge devices, we utilize typical logarithm utility functions [34] to capture the satisfaction degree of $\varphi_i(\Theta_i)$, i.e., $S_i(\Theta_i) = \xi_i \ln(1 + \varphi_i(\Theta_i))$. The satisfaction degree $S_i(\Theta_i)$ of the local AI service is considered as the obtain profit of the MEC node. Therefore, the utility of the MEC node is denoted as the total profits minus the incentive costs, which is shown as:

$$U^{MEC}(\boldsymbol{R}, \boldsymbol{\theta}) = \sum_{i \in \mathcal{M}} \xi_i \ln(1 + \varphi_i(\Theta_i)) - \sum_{j \in \mathcal{N}} R_j\theta_j \quad (15)$$

V. STACKELBERG GAME FORMULATION AND ANALYSIS

In our WPEG, we need to obtain the optimal power transmission and economic rewards to joint maximize the utility of both WPT nodes and the MEC node. To solve the joint optimization problems, we model the interaction between WPT nodes and the MEC node as a two-stage Stackelberg game. This two-stage game could be considered as energy-knowledge trading. That is, to obtain knowledge derived from the local data of edge devices, the MEC node needs to purchase energy from WPT nodes. At stage I, the MEC node acts as a leader in the upper game who sets economic reward strategies for each WPT node. At stage II, WPT nodes can be considered as followers in the sub-game who determine their power transmission strategies according to the given economic rewards. In general, we formulate our Stackelberg game model $\mathbb{G} = \{S_{i \in \mathcal{M}}^{MEC}, S_{j \in \mathcal{N}}^{WPT}; U_{i \in \mathcal{M}}^{MEC}, U_{j \in \mathcal{N}}^{WPT}\}$ as shown in the following:

- $S_{j \in \mathcal{N}}^{WPT}$ shows the strategy space of WPT nodes. The power transmission strategies of WPT nodes are $\theta = (\theta_1, \theta_2, ..., \theta_j, ..., \theta_N)$ ($\forall j \in \mathcal{N}$). Thus, we obtain that $S_{j \in \mathcal{N}}^{WPT} = \{\theta_j | 0 \leq \theta_j \leq \theta_j^{\max}; \forall j \in \mathcal{N}\}$. The transmission power θ_j should be non-negative and not to exceed the maximum transmission power $\theta_j^{\max}$. Similarly, $S_{i \in \mathcal{M}}^{MEC}$ denotes the incentive strategy space of the MEC node. The strategy space could be defined as $S_{i \in \mathcal{M}}^{MEC} = \{R_j | R_j^{\min} \leq R_j \leq R_j^{\max}; \forall i \in \mathcal{M}, j \in \mathcal{N}\}$.

- $U_{j \in \mathcal{N}}^{WPT}(R_j, \theta_j)$ is the utility function of the followers (i.e., WPT nodes), and $U_{i \in \mathcal{M}}^{MEC}(\boldsymbol{R}, \boldsymbol{\theta})$ is the utility function of the leader (i.e., the MEC node).

According to the above, at stage I, the objective optimization problem **P1** of the upper game for the MEC node could be described as follows:

$$\max_{(\boldsymbol{\theta}, \boldsymbol{R})} U^{MEC} = \sum_{i \in \mathcal{M}} \xi_i \ln[T_i^{\max} - \frac{\rho_i}{B\log_2(1+\frac{\kappa_i H_i}{N_0 B}\sum h_{ji}\theta_j)}$$

$$- \mathcal{O}(\log(\frac{1}{\delta_i}))\sqrt[3]{\frac{\mu_i c_i^3 d_i^3}{\kappa_i \sum h_{ji}\theta_j}} + 1] - \sum_{j \in \mathcal{N}} R_j \theta_j$$

$$s.t. \ R_j^{\min} \leq R_j \leq R_j^{\max} \ , \ \forall j \in \mathcal{N}$$

$$\theta_j^{\min} \leq \theta_j \leq \theta_j^{\max} \ , \ \forall j \in \mathcal{N}$$

$$0 < \delta_i < 1 \ , \ \forall i \in \mathcal{M}$$

In addition, at stage II, the objective optimization problem **P2** of the sub-game for WPT nodes could be formulated as:

$$\max_{(\theta_j, R_j)} \ U_j^{WPT} = R_j \theta_j - (a_j \theta_j^2 + b_j \theta_j + e_j)$$

$$s.t. \ R_j^{\min} \leq R_j \leq R_j^{\max} \ , \ \forall j \in \mathcal{N}$$

$$\theta_j^{\min} \leq \theta_j \leq \theta_j^{\max} \ , \ \forall j \in \mathcal{N}$$

$$0 < \delta_i < 1 \ , \ \forall i \in \mathcal{M}$$

It should be noted that the edge network status is dynamic, and some important information (e.g., channel conditions) will change with time. Thus, the Stackelberg game will perform periodic operations. After one period, the power transmission strategy and economic incentive strategy will be re-designed. We assume that WPT nodes will send channel conditions and energy cost factors to the MEC node, and edge devices will send the relevant learning parameters to the MEC node. So that the MEC node has complete information to derive the optimal strategy. And the scenario of asymmetric information is our future work.

A. Sub-Game of WPT Nodes

We apply the backward induction method to solve the joint problems (i.e., **P1** and **P2**). So we first analyse the power transmission sub-game of WPT nodes. The sub-game could be considered as a non-cooperative game between WPT nodes, and WPT nodes could dynamically adjusts the power transmission strategies to optimize the self-revenue.

Definition 1 (NE): In sub-game, the power transmission strategies $\boldsymbol{\theta}^* = (\theta_1^*, \theta_2^*, ..., \theta_j^*, ..., \theta_N^*)$ of WPT nodes is the Nash equilibrium (NE), if and only if $U_j^{WPT}(R_j^*, \theta_j, \Theta_{-j}) \leq U_j^{WPT}(R_j^*, \theta_j^*, \Theta_{-j})$, where Θ_{-j} is the power transmission strategy set of WPT nodes excluding θ_j.

Theorem 1: A unique Nash equilibrium exists in sub-game. And the optimal transmission power θ_j of WPT node j^* is:

$$\theta_j^* = \frac{R_j - b_j}{2a_j}, \quad \forall j \in \mathcal{N} \tag{16}$$

Proof: We find the first and second derivative of the utility function U_j^{WPT} with respect to θ_j as the following:

$$\frac{\partial U_j^{WPT}}{\partial \theta_j} = R_j - 2a_j \theta_j - b_j, \forall j \in \mathcal{N} \tag{17}$$

$$\frac{\partial^2 U_j^{WPT}}{\partial^2 \theta_j} = -2a_j < 0, \forall j \in \mathcal{N} \tag{18}$$

U_j^{WPT} is a strictly concave function about θ_j. And due to the boundedness of θ_j, **P2** should be a strict convex optimization

problem. Thus, a unique Nash equilibrium exists in sub-game. By solving $\partial U_j^{WPT}/\partial \theta_j = 0$, we could obtain Eq. (16).

Lemma 1: The optimal transmission power R_j^* of WPT node j satisfies $b_j \leq R_j^* \leq 2a_j \theta_j^{\max} + b_j$.

Proof: According to the definition of transmission power, we could have $\theta_j^* \geq 0$. Thus, $\theta_j^* = (R_j^* - b_j)/2a_j \geq 0$ and $R_j^* \geq b_j$ based on the Eq. (16). The lower bound of R_j^* is b_j. We also have $\theta_j \leq \theta_j^{\max}$. If $\theta_j^* = (R_j^* - b_j)/2a_j \leq \theta_j^{\max}$, we could obtain $R_j^* \leq 2a_j \theta_j^{\max} + b_j$. If $\theta_j^* = (R_j - b_j)/2a_j \geq \theta_j^{\max}$, thus $R_j \geq 2a_j \theta_j^{\max} + b_j$ and $\theta_j^* = \theta_j^{\max}$. By substituting θ_j^* into the upper game. U^{MEC} could be considered as a decreasing function about R_j. Thus, we have $R_j = 2a_j \theta_j^{\max} + b_j$. In general, $\theta_j^* \leq \theta_j^{\max}$ and $R_j \leq 2a_j \theta_j^{\max} + b_j$. The upper bound of R_j^* is $2a_j \theta_j^{\max} + b_j$. The proof is now completed. The optimal utility of WPT nodes could also be obtained as:

$$U_j^{WPT*} = \frac{(R_j - b_j)^2}{4a_j} - e_j, \ \forall j \in \mathcal{N}$$

$$s.t. \ b_j \leq R_j \leq 2a_j \theta_j^{\max} + b_j \tag{19}$$

B. Upper-Game of the MEC Node

Definition 2 (SE): In upper-game, the economic incentive strategies $\boldsymbol{R}^* = (R_1^*, R_2^*, ..., R_j^*, ..., R_N^*)$ of the MEC node is the Stackelberg equilibrium (SE), if and only if $U_j^{WPT}(R_j^*, \theta_j, \Theta_{-j}) \leq U_j^{WPT}(R_j^*, \theta_j^*, \Theta_{-j})$ and $U^{MEC}(\boldsymbol{R}, \boldsymbol{\theta}^*) \leq U^{MEC}(\boldsymbol{R}^*, \boldsymbol{\theta}^*)$.

Theorem 2: There exists a unique Stackelberg equilibrium between the leader and followers in our proposed game.

Proof: We will first substitute Eq. (16) into **P2**. **P2** in the upper game could be rewritten as follows:

$$\max_{(\boldsymbol{R})} U^{MEC} = \sum \xi_i \ln[T_i^{\max} - \frac{\rho_i}{B\log_2(1+\frac{\kappa_i H_i}{2a_j N_0 B}\sum h_{ji}(R_j - b_j))}$$

$$- \mathcal{O}(\log(\frac{1}{\delta_i}))\sqrt[3]{\frac{2a_j \mu_i c_i^3 d_i^3}{\kappa_i \sum h_{ji}(R_j - b_j)}} + 1]$$

$$- \sum R_j(R_j - b_j)/2a_j$$

$$s.t. \ b_j \leq R_j \leq b_j + 2a_j \theta_j^{\max} \ , \ \forall j \in \mathcal{N}$$

$$\theta_j^{\min} \leq \theta_j \leq \theta_j^{\max} \ , \ \forall j \in \mathcal{N}$$

$$0 < \delta_i < 1 \ , \ \forall i \in \mathcal{M}$$

In the above **P2**, we could easily observe that each term in the second summation is a quadratic function with respect to $\boldsymbol{R}$ (i.e., convex function). So we only need to investigate the first summation of the utility function U^{MEC}. In the first summation, each term represents the satisfaction degree $S_i(\boldsymbol{R}) = \xi_i \ln(1 + \varphi_i(\boldsymbol{R}))$. We now find the first derivative and the second derivative of $S_i(\boldsymbol{R})$ with regard to $\boldsymbol{R}$:

$$\frac{\partial S_i}{\partial R_m} = \xi_i \frac{1}{1 + \varphi_i(\boldsymbol{R})} \frac{\partial \varphi_i(\boldsymbol{R})}{\partial R_m} \tag{20}$$

$$\frac{\partial^2 S_i}{\partial^2 R_m} = \frac{-\xi_i}{(1 + \varphi_i)^2} \frac{\partial \varphi_i}{\partial R_m} \frac{\partial \varphi_i}{\partial R_m} + \frac{\xi_i}{1 + \varphi_i} \frac{\partial \varphi_i^2}{\partial^2 R_m} \tag{21}$$

$$\frac{\partial^2 S_i}{\partial R_m \partial R_n} = \frac{-\xi_i}{(1 + \varphi_i)^2} \frac{\partial \varphi_i}{\partial R_m} \frac{\partial \varphi_i}{\partial R_n} + \frac{\xi_i}{1 + \varphi_i} \frac{\partial \varphi_i^2}{\partial R_m \partial R_n} \tag{22}$$

$$H_i = -\left[\frac{\xi_i}{(1+\varphi_i(\boldsymbol{R}))^2}X_i^2 + \frac{\xi_i}{1+\varphi_i(\boldsymbol{R})}Y_i\right]\begin{pmatrix} h_{1i}h_{1i} & h_{1i}h_{2i} & \cdots & h_{1i}h_{Ni} \\ h_{2i}h_{1i} & h_{2i}h_{2i} & \cdots & h_{2i}h_{Ni} \\ \vdots & \vdots & \ddots & \vdots \\ h_{Ni}h_{1i} & h_{Ni}h_{2i} & \cdots & h_{Ni}h_{Ni} \end{pmatrix}_{N\times N}, \quad \forall i \in \mathcal{M} \tag{23}$$

$$\frac{\partial \varphi_i(\boldsymbol{R})}{\partial R_m} = h_{mi}\left[\sqrt[3]{\frac{2(\mathcal{O}(\log(1/\delta_i)))^3 a_j\mu_i c_i^3 d_i^3}{27\kappa_i(\sum h_{ji}(R_j-b_j))^4}} + \frac{\rho_i\kappa_i H_i \ln 2}{2a_j N_0 B^2(1+SNR_i)\ln^2(1+SNR_i)}\right] = h_{mi}X_i \tag{24}$$

$$\frac{\partial^2 \varphi_i(\boldsymbol{R})}{\partial R_m \partial R_m} = -h_{mi}h_{mi}\left[\frac{4}{9}\sqrt[3]{\frac{2(\mathcal{O}(\log(1/\delta_i)))^3 a_j\mu_i c_i^3 d_i^3}{\kappa_i(\sum_j h_{ji}(R_j-b))^7}} + \frac{\rho_i\kappa_i^2 H_i^2(\ln(1+SNR_i)+2)\ln 2}{4a_j^2 N_0^2 B^3(1+SNR_i)^2\ln^3(1+SNR_i)}\right] = -h_{mi}h_{mi}Y_i \tag{25}$$

$$\frac{\partial^2 \varphi_i(\boldsymbol{R})}{\partial R_m \partial R_n} = -h_{mi}h_{ni}\left[\frac{4}{9}\sqrt[3]{\frac{2(\mathcal{O}(\log(1/\delta_i)))^3 a_j\mu_i c_i^3 d_i^3}{\kappa_i(\sum_j h_{ji}(R_j-b))^7}} + \frac{\rho_i\kappa_i^2 H_i^2(\ln(1+SNR_i)+2)\ln 2}{4a_j^2 N_0^2 B^3(1+SNR_i)^2\ln^3(1+SNR_i)}\right] = -h_{mi}h_{ni}Y_i \tag{26}$$

Where $R_m, R_n \in \boldsymbol{R}$ and $R_m \neq R_n$. In addition, we derive the first derivative and the second derivative of $\varphi_i(\boldsymbol{R})$ with regard to $\boldsymbol{R}$, which is shown at the top of next page. To simplify, we utilize $SNR_i = \frac{\kappa_i H_i}{2a_j N_0 B}\sum h_{ji}(R_j - b_j)$ to present the Signal-Noise Ratio during communication. By substituting Eq. (24)-(26) into Eq. (20)-(22), we have:

$$\frac{\partial^2 S_i}{\partial^2 R_m} = \frac{-\xi_i}{(1+\varphi_i)^2}h_{mi}^2 X_i^2 + \frac{-\xi_i}{1+\varphi_i}h_{mi}^2 Y_i \tag{27}$$

$$\frac{\partial^2 S_i}{\partial R_m \partial R_n} = \frac{-\xi_i}{(1+\varphi_i)^2}h_{mi}h_{ni}X_i^2 + \frac{-\xi_i}{1+\varphi_i}h_{mi}h_{ni}Y_i \tag{28}$$

Where $X_i > 0$ and $Y_i > 0$, $\forall i \in \mathcal{M}$. Thus, we could get the Hessian matrix H_i of $S_i(\boldsymbol{R})$ through Eq. (27) (28), which is shown as Eq. (23). $-H_i$ is considered as a real symmetric matrix, which should be proved as a positive definite matrix, based on theorems in [43]. And we could prove H_i is a strict negative definite matrix, which shows the existence and uniqueness of the optimal strategy $\boldsymbol{R}^* = (R_1^*, R_2^*, ..., R_j^*, ..., R_N^*)$. Moreover, it also denotes that **P2** is a convex optimization problem. The proof is now completed.

To find the unique Nash equilibrium (NE) and Stackelberg equilibrium (SE) in our game, we design a low complexity gradient-based searching algorithm as **Algorithm 1**.

C. Optimal Learning Parameter Design

Benefit from the optimal transmission power $\boldsymbol{\theta}^*$ from WPT nodes, a stable and robust federated edge learning process can be guaranteed in our framework. But the global learning efficiency is still related to learning accuracy α (global) and δ_i (local). To maximize the learning efficiency of our framework, we now study how to design the optimal parameters. We assume that all edge devices have the same local accuracy $\delta_i = \delta$, $\forall i \in \mathcal{M}$. Thus global federated learning time T^{total} in our framework could be expressed as:

$$T^{total} = \frac{\mathcal{O}(\log(1/\alpha))}{1-\delta} \cdot \max\{T_i^{learn}(\delta, \boldsymbol{\theta}^*)\} \tag{29}$$

Algorithm 1 Optimal Incentive Reward and Power Transmission Algorithm

1: **Input:** a_j, b_j and e_j, $\forall j \in \mathcal{N}$; c_i, d_i, δ_i, $f_i^{\max}$, $\forall i \in \mathcal{M}$;
2: **Output:** $\boldsymbol{R}^*$, $\boldsymbol{\theta}^*$, U^{MEC*}, U_j^{WPT*}, $\forall j \in \mathcal{N}$;
3: **Initialization:** Maximum iteration number $\hat{t}$, step size σ;
4: **for** Each WPT node $j \in \mathcal{N}$ **do**
5:     Calculate $R_j^{\min}$ and $R_j^{\max}$ according to $R_j^{\min}=b_j$, and $R_j^{\max}=b_j + 2a_j\theta_j^{\max}$;
6: **end for**
7: Select initial input $\boldsymbol{R}^0 = (R_1^0, R_2^0, ..., R_j^0, ..., R_N^0)$, where $R_j^0 \in [R_j^{\min}, R_j^{\max}]$, $\forall j \in \mathcal{N}$, and $t = 0$;
8: **while** $t < \hat{t}$ **do**
9:     **for** Each WPT node $j \in \mathcal{N}$ **do**
10:         Calculate θ_j according to Eq. (16): $\theta_j^* = (R_j - b_j)/2a_j$;
11:     **end for**
12:     Update incentive rewards according to: $\boldsymbol{R}(t+1) = \boldsymbol{R}(t) - \sigma\nabla U^{MEC}(\boldsymbol{R}(t), \boldsymbol{\theta}^*(\boldsymbol{R}(t)))$;
13:     $t := t + 1$;
14: **end while**
15: Calculate $\boldsymbol{R}^*$, $\boldsymbol{\theta}^*$, U^{MEC*}, U_j^{WPT*} ($\forall j \in \mathcal{N}$) according to Eq. (13) (15) (16);

Let $t = \arg\max\{T_i^{learn}(\delta, \boldsymbol{\theta}^*)\}$, $t \in \mathcal{M}$ and $\mathcal{O}(\log(1/\delta)) = \beta\log(1/\delta)$, $\beta > 0$. Thus we could formulate the optimization problem **P3**, which is shown as follows.

$$\min_{\delta} T^{total} = \frac{\mathcal{O}(\log(1/\alpha))}{1-\delta}[T_t^{com} + \log(\frac{1}{\delta})Z_t(\boldsymbol{\theta}^*)]$$
$$s.t. \quad 0 < \alpha < 1; 0 < \delta < 1 \tag{30}$$

Where $T_t^{com}(\boldsymbol{\theta}^*)$ is the communication time of the edge device t, and $Z_t(\boldsymbol{\theta}^*) = \beta\sqrt[3]{\frac{\mu_t c_t^3 d_t^3}{\kappa_t \sum h_{jt}\theta_j^*}}$, $\forall j \in \mathcal{N}$.

Theorem 3: Under the optimal transmission power strategy $\boldsymbol{\theta}^*$, **P3** is a the convex problem and there exists a unique local training accuracy δ^* in our framework.

Lemma 2: $\log(1/\delta) > 0.5(1-\delta)(3-\delta)$, $\delta \in (0, 1)$

Proof: Let $G(\delta) = 0.5(1-\delta)(3-\delta) - \log(1/\delta)$, the first derivative of $G(\delta)$ with regard to δ is:

$$\frac{\partial G(\delta)}{\partial \delta} = \delta + \frac{1}{\delta} - 2 > 0, \ \delta \in (0,1) \tag{31}$$

Thus, $G(\delta) < G(1) = 0, \ \delta \in (0,1)$. The proof is completed. Let $A = \mathcal{O}(\log(1/\alpha)) > 0, \ \alpha \in (0,1)$, we now find the first and the second derivative of $T^{total}(\delta)$ as:

$$\frac{\partial T^{total}}{\partial \delta} = \frac{A[T_t^{com} + Z_t \log(1/\delta)]}{(1-\delta)^2} - \frac{AZ_t}{\delta(1-\delta)} \tag{32}$$

$$\frac{\partial^2 T^{total}}{\partial^2 \delta} = \frac{A[T_t^{com} + Z_t \log(1/\delta)]}{0.5(1-\delta)^3} - \frac{AZ_t(3\delta - 1)}{\delta^2(1-\delta)^2} \tag{33}$$

According to **Lemma 2**, we could have:

$$\frac{\partial^2 T^{total}}{\partial^2 \delta} > \frac{A[T_t^{com} + 0.5Z_t(1-\delta)(3-\delta)]}{0.5(1-\delta)^3} - \frac{AZ_t(3\delta - 1)}{\delta^2(1-\delta)^2}$$
$$= \frac{2AT_t^{com}}{(1-\delta)^3} + \frac{A\beta Z_t(1-\delta)}{\delta^2} > 0, \delta \in (0,1) \tag{34}$$

Therefore, **P3** is a strict convex optimization problem. The proof is now completed. We could calculate the optimal δ^* via classic one-dimensional convex optimization search method with convex optimization tools (e.g., cvxopt).

TABLE II: System Parameters in WPEG Framework

System parameters	Value setting
Number of edge devices $\mathcal{M}$	$M = [5, 100]$
Number of WPT nodes $\mathcal{N}$	$N = [5, 50]$
The transmission bandwidth of all the edge devices B	$B = 1$ MHz
The noise power spectrum density N_0	-174 dBm/Hz
Channel power gain h_{ij} and H_i	$32.44 + 20\lg(d)$
Data size of local weights/gradients ρ_i	$\rho_i = 1$ MB
The CPU cycles number for one sample data training c_i	[10, 30] cycles/bit
Data size of local personal dataset d_i	[25, 35] MB
The local sub-model trained accuracy δ_i of edge devices	$\delta_i \in (0, 1)$
The transmission energy cost factors of WPT nodes a_j and b_j	[0.6, 0.2]
The maximum transmission power θ_j^{max} of WPT nodes	$\theta_j^{max} = [2,3]$ W
The energy harvesting efficiency κ_i	$\kappa_i = [0.1, 0.9]$

VI. SIMULATION AND DISCUSSION

In this section, we conduct simulation experiments of our WPEG framework. Our experimental results mainly divide into three parts: 1) we compare our proposed optimal economic incentive strategy and power transmission strategy with several classic schemes in terms of the utility of the MEC node and the utility of WPT nodes, respectively; 2) we also study the influence of the number of edge devices, the number of WPT nodes, the energy harvesting efficiency on the performance of our framework; 3) we investigate the impact of learning parameter design on the performance of global learning efficiency in our framework. We conduct the federated learning simulation based on [5]. Some of the important simulation parameters settings are from [5], which are listed in **Table II**. Our simulation is conducted on Python 3.7 (numpy 1.18 and cvxopt 1.1) which based on the hardware of the 3.20 GHz I7 Intel processor and 16 GB RAM.

A. Experiment Setup in Our WPEG

1) Federated edge learning parameters: For each edge devices i ($i \in \mathcal{M}$), we set the training size d_i of each device as a uniform distribution in $25 - 35$ MB, CPU cycle number of one sample training c_i is a uniformly distributed in $10 - 30$ cycles/bit, the maximum computing resources of each device f_i^{max} is uniformly distributed in $3.0 - 4.0$ GHz. Furthermore, the data size of local weights and local gradients ρ_i is 1 MB.

2) Wireless power transfer parameters: we simulate a $200\,m \times 200\,m$ square area with M edge devices and N WPT nodes. The number of edge devices M is ranging from 5 to 100 and the number of WPT nodes N is ranging from 5 to 50. The MEC node is located at the center of the square area. Edge devices and WPT nodes are randomly distributed. Both of their horizontal and vertical coordinates follow the uniform distribution ranging from $-100\,m$ to $100\,m$. We also model the channel gain h_{ji} and H_i as the path loss model, i.e., $32.44 + 20\log_{10}(d)$, where d (meters) presents the distance in free space. The transmission bandwidth B of all the edge devices is set as 1 MHz and the noise power spectrum density N_0 is denoted as -174 dBm/Hz. The energy harvesting efficiency is set as $\kappa_i = [0.1, 0.9]$, respectively. And the energy cost factors of WPT nodes are $a_j = 0.6\text{W}^{-2}$, and $b_j = 0.2\text{W}^{-1}$. The maximum transmission power θ_j^{max} is a uniformly distributed in $2.0 - 3.0$ W.

B. Comparison Analysis with Other Learning Strategies

We compare our optimal learning strategy (i.e., the power transmission strategy and economic incentive strategy) with two different classic strategies, including random federated edge learning (RFEL) scheme and uniform federated edge learning (UFEL) scheme in terms of the utility of both parties in our framework.

- *Random federated edge learning (UFEL) scheme: 1)* The MEC node randomly provides economic incentives R_j^r to WPT nodes from $[R_j^{min}, R_j^{max}] (\forall j \in \mathcal{N})$ based on Eq. (19), and WPT nodes power edge devices with the optimal power transmission strategy θ_j^* according to Eq. (16); *2)* The MEC node rewards WPT nodes with the optimal economic incentive strategy R_j^*, while WPT nodes randomly determine the power transmission strategy from $(0, \theta_j^{max}] (\forall j \in \mathcal{N})$.
- *Uniform federated edge learning (UELS) scheme: 1)* The MEC node uniformly select economic incentives R_j^u to
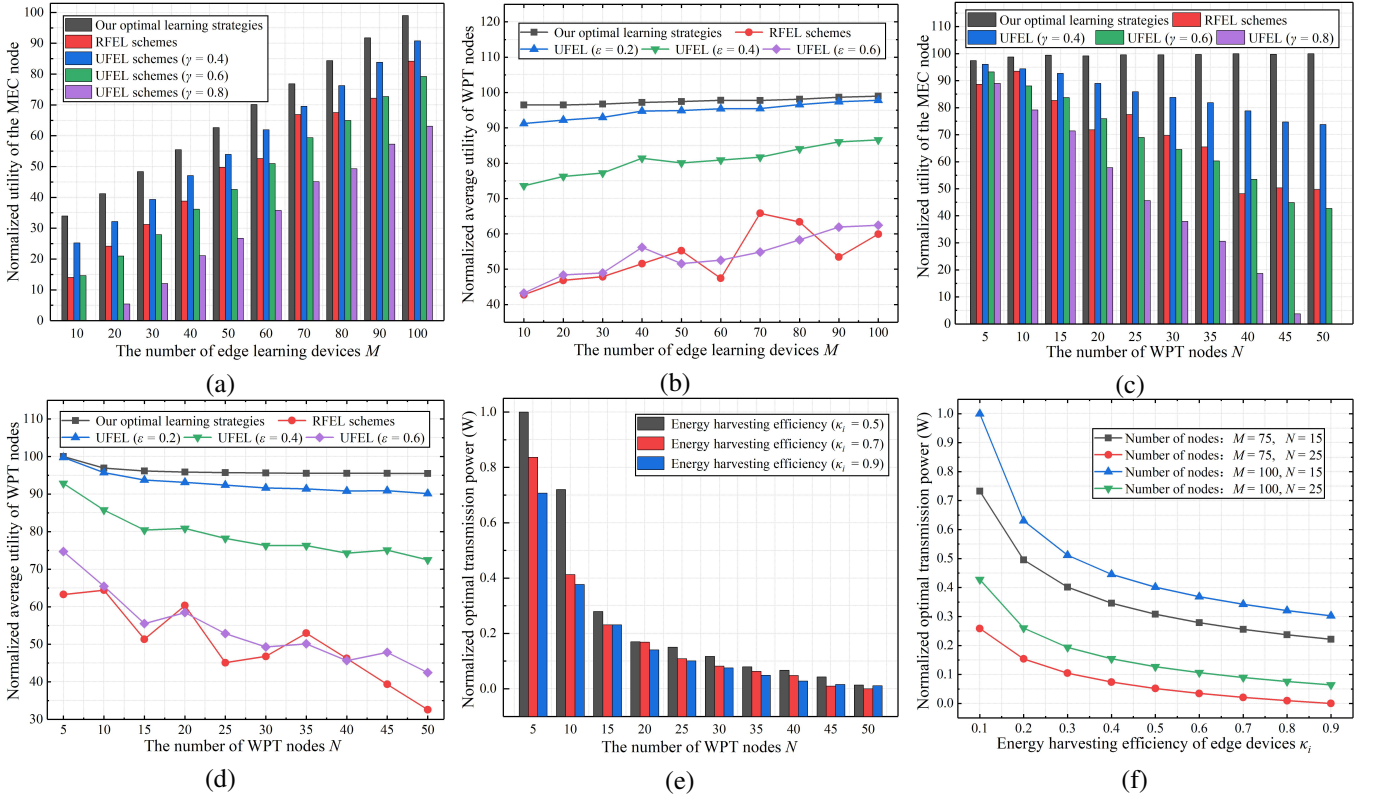
Fig. 4: (a) MEC node utility vs edge device number; (b) WPT node utility vs edge device number; (c) MEC node utility vs WPT node number; (d) WPT node utility vs WPT node number; (e) Transmission power vs WPT node number; (f) Transmission power vs energy harvesting efficiency

WPT nodes as $R_j^u = R_j^{\min} + \gamma(R_j^{\max} - R_j^{\min}) \, (\forall j \in \mathcal{N})$, where $\gamma = 0.4, 0.6, 0.8$, respectively, and WPT nodes charge edge devices with the optimal power transmission strategy θ_j^*; *2)* The MEC node grants WPT nodes with the optimal economic incentive strategy R_j^*, while WPT nodes uniformly adopt the power transmission strategy as $\theta_j^u = \theta_j^{\min} + \varepsilon(\theta_j^{\max} - \theta_j^{\min}) \, (\forall j \in \mathcal{N})$, where $\varepsilon = 0.2, 0.4, 0.6$, respectively.

We evaluate the performance of the above three learning strategies in terms of the utility of the MEC node and the average utility of WPT nodes, respectively, which are shown in Fig. 4. (a)-(d).

Specifically, Fig. 4. (a) (c) evaluate the economic pricing strategy. As shown in Fig. 4. (a), with the increase of edge learning devices, the utility of the MEC node has increased significantly. Because more devices bring more valuable data in federated learning, which improves the learning satisfaction of federated learning. Meanwhile, in terms of the average utility of the MEC node, compared with the RFEL and UFEL schemes, our optimal economic incentive strategy has increased by 32.38%, 14.42%, 41.37%, and 110.19%, respectively. Fig. 4. (c) evaluates the utility of MEC nodes as the number of WPT nodes changes. In our optimal strategy, the utility of the MEC node is relatively stable. This shows that simply increasing the number of WPT nodes could not improve the learning satisfaction of the MEC node. In this case, our optimal economic incentive strategy is improved by

42.35%, 16.70%, 46.94%, and 128.80% compared with the RFEL and UFEL schemes.

Fig. 4. (b) (d) investigate the power transmission strategy. As the number of edge devices increases, the utility of WPT nodes gradually increases as shown in Fig. 4. (b). This is because more edge devices require more energy to support the federated learning task. It will make MEC nodes trade more energy, which increases the utility of all WPT nodes. Besides, compared with the RFEL and UFEL schemes, our optimal power transmission strategy has increased 82.67%, 2.86%, 20.77%, and 81.28%, respectively. While the average utility of WPT nodes decreases when WPT nodes become more as shown in Fig. 4, (d). This is because when edge devices are fixed, the total energy required for learning is relatively fixed. When the number of WPT nodes increases, the average energy trading amount is lower. Thus, the average utility of WPT nodes is reduced. Similarly, our optimal power transmission strategy also improved by 91.55%, 3.52%, 21.43%, and 77.42% compared with the other two schemes.

C. Impact of Energy Harvesting Efficiency on Our Framework

In Fig. 4. (e) (f), we study the impact of energy harvesting efficiency κ_i on our learning system. As shown in Fig. 4. (e) (f), as the energy harvesting efficiency increases, the average power transmission of WPT nodes will decrease. Because when the energy conversion efficiency of edge devices is greater, WPT nodes only need to transmit less energy to
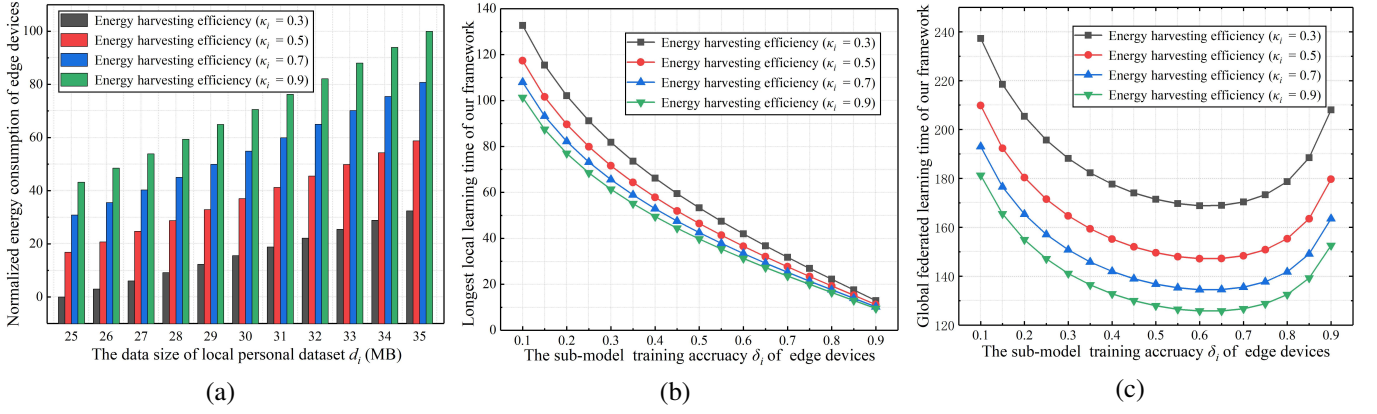
Fig. 5: (a) Energy consumption vs local dataset size; (b) local learning time vs local training accuracy; (c) Global learning time vs local training accuracy

meet the learning energy demands of edge devices. For WPT nodes, this also means the energy resource saving. At the same time, when the number of WPT nodes increases, the average transmission power of WPT nodes will further decrease. On the one hand, this is because the energy acquisition methods of edge devices are more decentralized and diversified, which reduces the transmission power of the single WPT node. On the other hand, in a limited spatial range, the denser WPT node deployment also means the average spatial distance between edge devices and WPT nodes is reduced. It will improve the energy channel gain and energy transmission efficiency, thus the transmission power of WPT nodes is reduced. When the number of edge devices is fixed and the number of WPT nodes is sufficient, the WPT nodes will charge edge devices according to the lowest power transmission strategy $\theta_j^{\min}$.

Meanwhile, as shown in Fig. 4. (f), when the number of edge devices decreases, the average power transmission of WPT nodes will also decrease accordingly. This is because when the number of edge devices is small, the energy requirement for learning is low. If the transmission power is too large and exceeds the energy demand of edge devices, edge devices can only adopt the largest computing resources $f_i^{\max}$ to learn, extra energy will be wasted. In this case, it is no longer energy resources that limits learning performance, but the computing resources of edge devices.

D. Impact of Learning Parameters Design on Global Learning Performance

In Fig. 5, we analyze the impact of learning parameter design on global learning performance in terms of learning energy consumption and learning time. As shown in Fig. 5. (a), as the local learning data size increases, the total learning energy consumption of edge devices will increase. Because when the local data size is larger, more local training is required, resulting in more energy consumption. However, the contribution of more data also means that edge devices will receive more rewards. We then show the relationship between local training accuracy and global learning time in Fig. 5. (b) (c). The global learning time, i.e., the total system efficiency, depends on global training accuracy α, local training accuracy

δ, and the longest training time in each local iteration $T_i^{\max}$. We let $\mathcal{O}(\log(1/\alpha)) = \varpi \log(1/\alpha)$, and make $\alpha = 0.2$ and $\varpi = 1$ without loss of generality. As shown in Fig. 5. (b), when the local accuracy δ increases, although the maximum time for local learning will be reduced, the corresponding local learning performance is reduced, resulting in an increase in the number of global iteration cycles. As shown in Fig. 5. (c), the local training accuracy and the global learning time are convexly related, that is, there is a unique trade-off to balance the local training accuracy and the global learning time. And we can easily obtain the optimal local accuracy δ^*. In actual applications, we will adopt the optimal learning parameter design to maximize the efficiency of the system.

VII. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a novel robust-efficient W-PEG framework and investigated a joint optimization of power transfer, learning design, and user incentives for maximizing system efficiency and multi-user profits. In the framework, we have first employed a permissioned edge blockchain to manage the P2P energy and knowledge sharing process in a secure and efficient manner. Besides, we have studied wirelessly-powered computing and communication models in edge AI, and characterized how wireless power transfer affects the latency and energy consumption of edge AI. Based on this, we have designed an energy-knowledge trading Stackelberg-game model to obtain the optimal power transmission and user incentives for our framework. Furthermore, the trade-off between the learning parameter and the global system efficiency has been studied and the uniqueness of the optimal learning parameter design has been proved. Numerical results have demonstrated that the game-based energy-knowledge incentive strategies could optimize the utilities of both parties in our framework, and attract WPT nodes charging edge devices to ensure robust-efficient edge learning process. In addition, numerical results also have proved our optimal learning parameter design could achieve the optimal global learning efficiency. In future works, we will further consider user mobility with more effective incentives and resource allocation in our WPEG framework, which will enhance better network stability.

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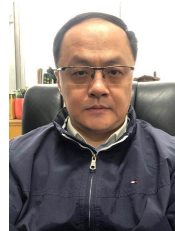
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