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Bargaining Game-Based Resource Management for Pervasive Edge Computing Infrastructure

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ABSTRACT The explosive growth of Internet of things (IoT) devices has promoted the prosperity of virtual reality applications, which can be realized by service offloading with the assistance of pervasive edge computing (PEC) platforms. However, owing to the limited computational and communication resources of PEC systems, it is necessary to design a novel resource management algorithm. In this study, we adopt cooperative bargaining theory to design our PEC resource allocation scheme. According to the concept of *unification bargaining solution*, different bargaining ideas are reciprocally combined to provide a fair-efficient solution. By coordinating network agents, we can leverage mutual consensus and approximate a well-balanced system performance among conflicting requirements. It is essential to explore the relevant trade-off between efficiency and fairness. To effectively share the PEC resources, the main novelty of our approach is its adaptability and flexibility to respond dynamic PEC system environments. Finally, extensive simulations are carried out, and the numerical results demonstrate that our unified bargaining method can obtain desirable features while maximizing the offloading service performance by comparing the existing state-of-the-art PEC control protocols.


INDEX TERMS Pervasive edge computing, Internet of Things, unification bargaining solution, computation offloading, cooperative game theory.

I. INTRODUCTION

With the rapid development of 5G network technology, communication and computation have undergone significant changes. Technologies such as the Internet of things (IoT), cloud and edge computing, tactile Internet, terahertz, and blockchain have brought new business models and markets. These technologies have several advantages in many sectors and a series of new concepts have been proposed. With these new concepts, IP-based networking devices have become increasingly efficient and complex. Over the last decade, mobile and IoT devices have become indispensable parts of our daily activities. Alongside the IoT evolution, the number of connected smart devices has skyrocketed, and it is expected to experience a many-fold increase by 2025. Within this setting, heterogeneous devices have a wide range of computational capabilities, and they are predicted

to execute various applications with different constraints and requirements [1], [2].

In IoT networks, computation-intensive and latency-sensitive mobile applications, such as virtual reality (VR), pose great challenges to resource-limited IoT devices. Wireless VR is predicted to become a killer application in 5G and beyond, providing an immersive experience and revolutionizing the way people communicate. Rendering is a key performance bottleneck in wireless VR systems, particularly in VR games. Typically, VR games involve various foreground interactions and rich-detail background environment rendering. Therefore, mobile IoT devices with considerable computational resources are required to provide high quality-of-experience (QoE). However, despite recent hardware advances in smart devices, they are not yet capable of efficiently supporting computation-intensive VR applications, because their local computing power and energy resources remain insufficient. Technically, this indicates that local rendering on today's mobile device hardware may not

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support untethered VR users' QoE requirements, i.e., 14 ms latency and 60 frames per second. Therefore, despite growing market penetration, today's high-end VR systems remain tethered [6].

For future 5G and beyond networks, the delivery of VR videos with a high QoE is one of the main challenges. To address the limitations of the current IoT devices, pervasive edge computing (PEC) is a new paradigm in information and communication technologies. In a timely manner, it can provide the support required for processing urgent and complex tasks. With PEC, a portion of rendering tasks can be offloaded to computing-assisted edge servers, which will support wireless VR. Unlike conventional edge computing methods, the advantages of PEC can be summarized as follows: i) no central authority is required to enable feasible and diverse applications, ii) it is infrastructure-free for deploying and maintaining the dedicated cloud backend, iii) data can be processed near end-users to reduce the transmission delay, and iv) privacy and security issues are well addressed. Therefore, the PEC paradigm is more suitable for future network scenarios and is responsible for decentralized decision-making, information security, high accuracy, and data transmission rates for resource-constrained IoT devices. In recent years, the applications of PEC have spread widely from entertainment to industry such as live games, multi-angle video viewing, and cooperative driving [2]–[5].

As a pivotal technology, the PEC has attracted significant attention in both academia and industry. However, although the PEC paradigm can be assumed to be a possible solution with promising ideas, some challenges still need to be addressed. First, under economic deployment constraints, each individual edge server has limited computing capability. Therefore, it is not appropriate for an edge server to deal with all rendering tasks. With an effective computational control strategy, the system efficiency should be improved. Second, the scarcity of wireless bandwidth can be a bottleneck in wireless VR. In general, the data rate for carrying an immersive VR video is typically over 25 Mbps. Under time-varying network environments, this metric is difficult to satisfy, especially in the face of data traffic congestion [6], [7].

In a multi-device interactive environment, each individual IoT device is an autonomous, distributed and intelligent network agent, and intends to maximize its own payoff, which is consistent with its preferences among different alternative outcomes. In this situation, many researchers have focused on ensuring the fairness of devices in a fully decentralized environment while providing the required QoE. However, this is a complex and difficult task in dynamic PEC environments. Therefore, a new intelligent control paradigm with novel solution concepts is required. Multiple IoT devices should be guided to make rational and strategic decisions to reach a fair-efficient consensus. In this scenario, cooperative game theory deserves to be investigated to design novel PEC system control algorithms [8].

A. TECHNICAL CONCEPTS

The game theory is a mathematical theory of interactive decision situations with strategic settings. In one of these situations, some players make decisions depending on the outcome results, and each player has his/her own preferences for the set of possible outcomes. From a non-cooperative view, the strategic analysis of games is concerned. In this case, players make decisions independently and are not able to form binding commitments. Therefore, players look for the best strategies considering that others will also behave by searching for their best. In other cases, cooperative games focus on how players share the benefits of their cooperation. This approach assumes that players have a mechanism to enforce their coordination. Almost seventy years ago, J. Nash studied cooperative game theory and published his pioneered seminal paper on the static axiomatic approach. Since then, several new bargaining solutions have been introduced to supplement the original Nash solution [8], [9].

Nash bargaining solution (NBS) is the first cooperative game solution with axiomatic characterizations. It can predict the outcome of the bargaining process based only on information regarding each player's preferences. The *NBS* is formulated by an expected utility function over the set of feasible agreements and the outcome which would result in disagreement. The *egalitarian bargaining solution (EBS)* and *utilitarian bargaining solution (UBS)* are alternative solutions to bargaining problems. The main difference between these three bargaining solutions is the viewpoint of how to compromise between egalitarianism and utilitarianism. To begin the search for appropriate solutions to multi-criteria problems, *NBS*, *EBS*, and *UBS* negotiate with these two opposing axiomatic principles. In *NBS*, if the bargaining solution of the larger set is found in a smaller domain, the solution is not affected by the domain size. However, the *EBS* attempts to grant equal gains to all the players. In other words, this is the point that maximizes the minimum payoff among players. On the other hand, the *UBS* attempts to maximize the total sum of players' payoffs, after having utility functions [8], [10].

The *unification bargaining solution (UniBS)* was introduced by C. Haakea and C. Qin to clarify what could be a reasonable solution if cooperative game players have different notions about the ideal solution. It is worth remarking that *UniBS* includes *NBS*, *EBS* and *UBS* as special cases under which a bargaining solution can be found for the multi-criteria bargaining problem. The key unifying axiom for *UniBS* specifies how the ratios of players' payoff gains in the solutions of the transformed problems via affine transformations respond to the ratios of players' payoff scales resulting from the transformations. Therefore, *UniBS* is characterized by a control parameter that measures the degree of balance between individual and collective orientations [11].

B. MAIN CONTRIBUTIONS

In this study, we exploit a PEC platform with computation offloading technology. Based on heterogeneous IoT devices and multi-edge server environments, each IoT device can partially offload its computational workload to the corresponding PEC server for remote execution. To design a new computation offloading algorithm for the PEC infrastructure, our major objective is to effectively share limited PEC resources under dynamically changing PEC environments. To satisfy this goal, multiple IoT devices and their corresponding servers work together and act cooperatively to enhance the conflicting performance criteria.

In the proposed algorithm, the limited computational and communication resources of the PEC platform are adaptively shared among individual IoT devices. To solve these resource sharing problems, we adopt the idea of *UniBS* and implement our unified bargaining process, which is traced back to a sequential negotiation between a device and edge pair. Each individual device focuses on a strategy to maximize its payoff, but the device-edge pair also shares a common goal and makes a binding commitment based on the exchange of current information. Therefore, the strategies of the devices and edge are coupled. In our unifying bargaining game model, this feature can play a significant role in determining the system performance. To the best of our knowledge, this is the first study in which different bargaining concepts are selectively applied to the design of PEC resource allocation algorithm. The key contributions of this paper are summarized as follows:

- We introduce a PEC platform to provide computation offloading services. In widely different and diversified system environments, individual IoT devices and edge servers participate in a unified bargaining process to provide a more fair-efficient control method.
- We study the fundamental idea of *NBS*, *EBS* and *UBS* and develop our bargaining game model based on the idea of *UniBS*. According to the current system conditions, different bargaining solutions can be selectively applied to the PEC resource allocation problem.
- To handle the computation offloading problem, communication and computation resources in the PEC system are effectively shared in a coordinated manner. Therefore, control decisions are coupled to get a desirable solution while ensuring the relevant trade-off between egalitarianism and utilitarianism.
- We demonstrate the superiority of our proposed algorithm from an experimental perspective. The performance results provide useful guidance to confirm the effectiveness of our proposed unified bargaining approach by comparing it with existing state-of-the-art protocols.

II. RELATED WORK

In this section, we first present a brief introduction to state-of-the-art resource control protocols on PEC platforms. Subsequently, the distinction between the existing work and

our proposed method is specified. In [15], a new blockchain system is adapted to address the limitations of edge devices. It can fairly and efficiently allocate storage resources on edge devices, and reaches consensus with low energy consumption in edge devices with a new proof-of-stake mechanism [15]. The paper [16] has proposed a fair and data producer profit protecting data trading mechanism in pervasive edge computing environments. It is a smart-contract based protocol that ensures the profit of the producer for reselling. Based on the two-stage dynamic Stackelberg game, this study can find a fair revenue sharing ratio between the data producer and the resellers, and has proved the approximation ratio between the rounded result and the optimal integer result [16].

Y. Huang *et al.* study the unique problem of caching fairness in edge computing environments [17]. They propose fairness metrics to characterize this issue and formulate the caching fairness problem as an integer linear programming problem. Their approach can achieve comparable or even lower latency while greatly improving fairness, and thus, data access robustness and performance [17]. In [18], a new quality-of-experience (QoE) model is proposed for evaluating the quality of services in a pervasive edge computing environment. To realize the high accuracy of high-dimensional big data and the transmission of accurate data throughout the pervasive edge computing environment, this paper focuses on two aspects: i) the issue as a high-dimensional big data management problem, and ii) testing different transmission rates to acquire the best QoE. It is suitable for high-dimensional big data analysis in a pervasive edge computing environment [18].

Security breaches may cause potentially harmful problems in PEC systems. Therefore, it is important to implement appropriate security mechanisms and safeguard the PEC resources from intrusion. In recent years, attacks targeting PEC infrastructure have drastically increased, and ensuring the privacy of sensitive PEC data is far more difficult than ever before. In particular, Sybil, denial-of-service (DoS), man-in-the-middle attacks are the most notable attacks. Papers [19]–[21] conduct a comprehensive survey on the security aspects of the PEC paradigm, identifying their threat models, such as information security, cyber security, forensic security, and network security. These survey papers have presented a thorough study on the recent research and technological development in the area of PEC security and its application domains, research challenges, and open issues [19]–[21].

Lin *et al.* propose the *Pervasive Edge Computing Resource Management (PECRM)* scheme for a VR-supported industrial IoT platform [7]. They formulate the service task offloading and resource allocation process as an optimization problem. Then, this optimization problem is transformed into a sequential decision making problem under time-varying channel conditions. By considering the VR QoE, the decision making problem is modeled as a Markov decision process (MDP) to maximize the long-term system reward. To tackle this MDP efficiently, a quantum-inspired

reinforcement learning algorithm is designed to find the optimal policy in an online fashion while improving the learning efficiency. In the simulations, they evaluate the performance to show that the *PECRM* scheme achieves better performance than other baseline schemes [7].

In [5], the *Decentralized Multi Agent Computation Offloading (DMACO)* scheme allows IoT devices to make decisions on the network edge without centralized management. From the viewpoint of each individual device, it is challenging to select an appropriate edge server to offload tasks. In a multi-device environment, each device aims to maximize its own utility. By considering the communication and computation abilities of edge devices, the *DMACO* scheme formulates the task scheduling process in a PEC environment as an optimization problem. Usually, guaranteeing the task completion time is difficult without reasonable task allocation strategies. To address this issue, the *DMACO* scheme develops a decentralized computation offloading algorithm to minimize the average task completion time in the PEC platform. This approach is a prior attempt to leverage the generalized adversarial imitation learning in a multi-agent PEC environment. Finally, the performance results demonstrate the effectiveness of the *DMACO* scheme in terms of average task completion time, convergence time and offloading ratios [5].

The *Pervasive Edge Computing Service Placement (PECSP)* scheme is a dynamic service placement framework for efficient offloading services on a PEC platform [12]. To enable dynamic service placement, the Lyapunov optimization method is used to decompose the long-term optimization problem into a series of online Lyapunov drift-plus-penalty minimization problems. Then, a sample average approximation-based stochastic algorithm is proposed to approximate the future expected system utility. Without prior knowledge of future movement trajectories of IoT devices, the future system utility is approximated by Monte-Carlo based stochastic sampling. In addition, the *PECSP* scheme provides the service placement probability distribution and convex log-sum-exp function to transform the system utility maximization problem into a Markov approximation optimization problem. Therefore, the storage capability of PEC servers can be fully utilized. Finally, performance evaluations demonstrate the effectiveness and efficiency of the *PECSP* scheme in terms of system utility, service fraction and convergence time [12].

To date, some resource allocation schemes have been proposed using new ideas. Referring to the advantages of existing work, we construct a novel unified bargaining method for the PEC resource allocation problem. For the PEC platform, the main contribution of our scheme is the reciprocal combination of different bargaining ideas to provide a fair-efficient solution. Owing to the desirable features of cooperative game theory, our approach based on *UniBS* can achieve globally desirable PEC system performance while dynamically adapting to the IoT network environment.

III. THE PROPOSED PEC RESOURCE ALLOCATION ALGORITHM

In this section, PEC system infrastructure and operational scenarios are introduced. Then, the proposed bargaining game is formulated based on *UniBS* to share PEC resources. Finally, we describe the main steps of our proposed algorithm.

A. IoT-BASED PEC PLATFORM AND UNIFIED BARGAINING GAME

In this study, we assume a PEC system platform consisting of multiple PEC servers, $\mathbb{E} = \{\varepsilon_1, \dots, \varepsilon_n\}$, which provide computational services for a set of IoT devices, $\mathbb{D} = \{\mathcal{D}_1, \dots, \mathcal{D}_m\}$. Individual PEC servers are connected via high speed fiber communications, and are endowed with edge computing capabilities. Each device can offload its computational tasks to the corresponding PEC server via wireless communications. The computing capability of $\varepsilon_{1 \leq i \leq n}$ is characterized by its computation service rate, that is the CPU frequency. Each ε_i serves a dedicated set of IoT devices in its serving area, denoted by $\mathbb{D}_{\varepsilon_i} \subseteq \mathbb{D}$. IoT devices are authorized to access the communication and computing services of the deployed PEC server. The totally generated computation workload for the $\mathcal{D}_{1 \leq j \leq m}$ is $\Upsilon_{\mathcal{D}_j}$ where $\Upsilon_{\mathcal{D}_j} = \Upsilon_{\mathcal{D}_j}^{\varepsilon_i} + \Upsilon_{\mathcal{D}_j}^L$ where $\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}$ and $\Upsilon_{\mathcal{D}_j}^L$ are the \mathcal{D}_j 's offloading and local computation amounts, respectively. In our bargaining game model, the $\varepsilon - \mathcal{D}$ association is a game entity that negotiates with each other in a cooperative manner.

The operational timeline is discretized into time slots to make offloading decisions, which is the same time scale as the task arrivals. In each time slot, computation tasks originating from each IoT device are generated according to a Poisson process, which is a common assumption for computation task arrival in the PEC system. IoT devices may request different types of tasks that vary in input data size and required CPU cycles. Because task workload arrivals are often uneven among IoT devices, tasks can be partially offloaded for processing. For computation offloading services, data transmissions occur in the wireless link between the device and its corresponding edge server. However, the computing power and wireless bandwidth of PEC servers are limited. Therefore, offloading strategies should consider the current system situation to improve the resource efficiency [13].

To address the PEC resource sharing problem, we formulate three bargaining games. At a time period, each individual $\mathcal{D}_{1 \leq j \leq m}$ and $\varepsilon_{1 \leq i \leq n}$ processes their bargaining games. In the \mathcal{D}_j , the $\Upsilon_{\mathcal{D}_j}$ is partially offloaded to increase the \mathcal{D}_j 's profit, and the bargaining game $(\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i})$ is designed to divide the $\Upsilon_{\mathcal{D}_j}$. In the ε_i , two bargaining games, i.e., $\mathbb{G}_{\varepsilon_i}^\Gamma$ and $\mathbb{G}_{\varepsilon_i}^\Theta$, are formulated to share the ε_i 's computation (Γ_{ε_i}) and communication (Θ_{ε_i}) resources, respectively. Based on the concept of *UniBS*, the $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$, $\mathbb{G}_{\varepsilon_i}^\Gamma$ and $\mathbb{G}_{\varepsilon_i}^\Theta$ are operated in a cooperative manner, and are repeated in a step-by-step interactive fashion at each time period. Formally, we define the $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$, $\mathbb{G}_{\varepsilon_i}^\Gamma$ and $\mathbb{G}_{\varepsilon_i}^\Theta$ game

entities, i.e.,

$$\begin{aligned} \mathbb{G} &= \left\{ \mathbb{G}_{\mathcal{D}_1}^{\varepsilon_i}, \mathbb{G}_{\varepsilon_1}^{\Gamma}, \mathbb{G}_{\varepsilon_1}^{\Theta} \right\} \\ &= \left\{ \mathbb{E}, \mathbb{D}, \left\{ \mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i} \mid \mathfrak{M}_{\mathcal{D}_j}, \left(\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}, \Upsilon_{\mathcal{D}_j}^L \right), U_{\mathcal{D}_j}^O(\cdot), U_{\mathcal{D}_j}^L(\cdot) \right\}, \right. \\ &\quad \times \left\{ \mathbb{G}_{\varepsilon_i}^{\Gamma} \mid \Gamma_{\varepsilon_i}, \mathbb{D}_{\varepsilon_i}, \Gamma_{\varepsilon_i}^{\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}}, \mathcal{U}_{\mathcal{D}_j}(\cdot) \right\}, \\ &\quad \left. \times \left\{ \mathbb{G}_{\varepsilon_i}^{\Theta} \mid \Theta_{\varepsilon_i}, \mathbb{D}_{\varepsilon_i}, \Theta_{\varepsilon_i}^{\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}}, \mathcal{U}_{\mathcal{D}_j}(\cdot) \right\}, T \right\} \end{aligned}$$

of gameplay.

- The $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$, $\mathbb{G}_{\varepsilon_i}^{\Gamma}$ and $\mathbb{G}_{\varepsilon_i}^{\Theta}$ are mutually and reciprocally interdependent in an interactive manner, and work together to share PEC resources.
- \mathbb{E} is the set of edge servers, and \mathbb{D} is the set of IoT devices in the PEC system platform.
- In the $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$, $\mathfrak{M}_{\mathcal{D}_j}$ is the total computing capacity of \mathcal{D}_j , and offloading and local computing services are game players. $\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}$ and $\Upsilon_{\mathcal{D}_j}^L$ are their strategies, and $U_{\mathcal{D}_j}^O(\cdot)$ and $U_{\mathcal{D}_j}^L(\cdot)$ are their utility functions.
- In the $\mathbb{G}_{\varepsilon_i}^{\Gamma}$, Γ_{ε_i} is the ε_i 's total computation capacity, and IoT devices in the $\mathbb{D}_{\varepsilon_i}$ are game players. $\Gamma_{\varepsilon_i}^{\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}}$ is the \mathcal{D}_j 's strategy and $\mathcal{U}_{\mathcal{D}_j}(\cdot)$ is its utility function.
- In the $\mathbb{G}_{\varepsilon_i}^{\Theta}$, Θ_{ε_i} is the ε_i 's total communication capacity, and IoT devices in the $\mathbb{D}_{\varepsilon_i}$ are game players. $\Theta_{\varepsilon_i}^{\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}}$ is the \mathcal{D}_j 's strategy and $\mathcal{U}_{\mathcal{D}_j}(\cdot)$ is its utility function.
- The discrete time model $T \in \{t_1, \dots, t_c, t_{c+1}, \dots\}$ is represented by a sequence of time steps. The length of t_c matches the event time-scale of $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$, $\mathbb{G}_{\varepsilon_i}^{\Gamma}$ and $\mathbb{G}_{\varepsilon_i}^{\Theta}$.

B. THE FUNDAMENTAL IDEA OF THE UNIBS

To characterize the basic concepts of bargaining solutions, we assume an n -player bargaining problem. Let $N = \{1 \dots i \dots n\}$ be the set of players and let \mathbb{R}^n denote the n -dimensional Euclidean space. Given vectors $x, y \in \mathbb{R}^n$, $x \geq y$ and $x \gg y$ if $x_i \geq y_i$ and $x_i > y_i$ for all i , respectively. Set $\mathbb{R}_+^n = \{x \in \mathbb{R}^n \mid x \geq 0\}$ and let S and d be the set of feasible outcomes and disagreement point, respectively, where $S \subset \mathbb{R}^n$ and $d \in S$. Let Σ be the set of all subsets of \mathbb{R}_+^n , and elements in Σ are interpreted as bargaining problems. Mathematically, the *NBS* can be defined as follows [11]:

$$NBS(S) = \max_{i \in N, S \in \Sigma} \left\{ u_i \in S \mid \begin{matrix} (u_1 - d_1) \times \dots \times \\ (u_i - d_i) \times \dots \times (u_n - d_n) \end{matrix} \right\} \quad (1)$$

The *EBS* can be computed via the following maximization problem [11]:

$$EBS(S) = \max_{i \in N} \left\{ u_i \in S \mid \min_{S \in \Sigma} \left((u_1 - d_1), \dots, (u_i - d_i), \dots, (u_n - d_n) \right) \right\} \quad (2)$$

The *UBS* can be defined as follows [11]:

$$UBS(S) = \max_{i \in N, S \in \Sigma} \left\{ u_i \in S \mid \left((u_1 - d_1) + \dots + (u_i - d_i) + \dots + (u_n - d_n) \right) \right\} \quad (3)$$

To unify the different bargaining solutions, *unification function (UF)* can be defined with a control parameter ε where $\varepsilon \in (0, 1) \cup (1, \infty)$. A new bargaining solution, called *UniBS*, is obtained by maximizing the *UF*, which includes *NBS*, *EBS* and *UBS* as special cases [11].

$$\begin{aligned} UF(u_i \in S \mid \varepsilon) &= \left[(u_1 - d_1)^{\frac{\varepsilon-1}{\varepsilon}} + \dots + (u_i - d_i)^{\frac{\varepsilon-1}{\varepsilon}} \right. \\ &\quad \left. + \dots + (u_n - d_n)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \\ \text{s.t., } \lim_{\varepsilon \rightarrow \bar{\varepsilon}} UF(u_i \in S \mid \varepsilon) &= \begin{cases} EBS, & \text{if } \bar{\varepsilon} = 0 \\ NBS, & \text{if } \bar{\varepsilon} = 1 \\ UBS, & \text{if } \bar{\varepsilon} = \infty \end{cases} \quad (4) \end{aligned}$$

C. THE UNIFIED BARGAINING GAME IN THE PEC PLATFORM

To develop new unified bargaining game models, we construct the $\mathbb{G}_{\mathcal{D}_i}^{\varepsilon_i}$, $\mathbb{G}_{\varepsilon_i}^{\Gamma}$ and $\mathbb{G}_{\varepsilon_i}^{\Theta}$ games. They interact with each other during a sequence of time steps. At each time period, the $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$ is designed for the $\varepsilon_i - \mathcal{D}_j$ pair; the \mathcal{D}_j partially offloads its computation task to the ε_i . This game decides the computation offloading size, that is $\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}$, to maximize the \mathcal{D}_j 's payoff. As game players, offloading and local computing services select their strategies, i.e., $\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}$ and $\Upsilon_{\mathcal{D}_j}^L$, by considering the currently available \mathcal{D}_j 's computing power and the ε_i 's offloading cost. At time t_c , the utility functions of offloading computing service ($U_{\mathcal{D}_j}^O(\cdot)$) and local computing service ($U_{\mathcal{D}_j}^L(\cdot)$) are defined as follows:

$$\begin{aligned} &\left\{ \begin{aligned} U_{\mathcal{D}_j}^O(\Upsilon_{\mathcal{D}_j}, \Upsilon_{\mathcal{D}_j}^{\varepsilon_i}, c_{t_c}^{\varepsilon_i}) &= \\ \exp\left(-\frac{\min(\Upsilon_{\mathcal{D}_j}, \Upsilon_{\mathcal{D}_j}^{\varepsilon_i})}{\Upsilon_{\mathcal{D}_j}} \times c_{t_c}^{\varepsilon_i}\right) &\times \Upsilon_{\mathcal{D}_j}^{\varepsilon_i} \end{aligned} \right. \\ &\left\{ \begin{aligned} U_{\mathcal{D}_j}^L(\Upsilon_{\mathcal{D}_j}, \Upsilon_{\mathcal{D}_j}^L, \rho_{t_c}^{\mathcal{D}_j}) &= \\ \left[\eta - \log\left(\frac{\min(\Upsilon_{\mathcal{D}_j}, \Upsilon_{\mathcal{D}_j}^L)}{\Upsilon_{\mathcal{D}_j}} + \rho_{t_c}^{\mathcal{D}_j}\right) \right] &\times \Upsilon_{\mathcal{D}_j}^L \end{aligned} \right. \\ &\text{s.t., } \Upsilon_{\mathcal{D}_j} = \Upsilon_{\mathcal{D}_j}^{\varepsilon_i} + \Upsilon_{\mathcal{D}_j}^L, \\ &c_{t_c}^{\varepsilon_i} = \frac{\mathcal{M}_{\varepsilon_i}^{t_c}}{\Gamma_{\varepsilon_i}} \text{ and } \rho_{t_c}^{\mathcal{D}_j} = \exp\left(\frac{\Upsilon_{\mathcal{D}_j}}{\mathfrak{M}_{\mathcal{D}_j}}\right) \quad (5) \end{aligned}$$

where $c_{t_c}^{\varepsilon_i}$ is the ε_i 's offloading computational cost, $\rho_{t_c}^{\mathcal{D}_j}$ is the \mathcal{D}_j 's working-load status, and $\mathcal{M}_{\varepsilon_i}^{t_c}$ is the using computing power of ε_i , at time t_c . Therefore, $c_{t_c}^{\varepsilon_i}$ and $\rho_{t_c}^{\mathcal{D}_j}$ may increase in direct proportion to the current computational overhead, and η is a control parameter for $U_{\mathcal{D}_j}^L(\cdot)$. Because all game players in the $\mathbb{G}_{\mathcal{D}_i}^{\varepsilon_i}$ are components of \mathcal{D}_i , the solution concept of $\mathbb{G}_{\mathcal{D}_i}^{\varepsilon_i}$ should be strongly concerned with egalitarianism for game players. In this case, the *EBS* is preferred for the \mathcal{D}_i .

It is given by:

$$\begin{aligned} & \lim_{\varepsilon \rightarrow 0} UF \left(U_{\mathcal{D}_j}^O(\cdot), U_{\mathcal{D}_j}^L(\cdot), \Upsilon_{\mathcal{D}_j}, (d_{\mathcal{D}_j}^O, d_{\mathcal{D}_j}^L) \mid \varepsilon \right) \\ &= \left[\left(U_{\mathcal{D}_j}^O(\cdot) - d_{\mathcal{D}_j}^O \right)^{\frac{\varepsilon-1}{\varepsilon}} + \left(U_{\mathcal{D}_j}^L(\cdot) - d_{\mathcal{D}_j}^L \right)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \\ &\cong \max \left[\min \left\{ \left(U_{\mathcal{D}_j}^O(\cdot) - d_{\mathcal{D}_j}^O \right), \left(U_{\mathcal{D}_j}^L(\cdot) - d_{\mathcal{D}_j}^L \right) \right\} \right] \quad (6) \end{aligned}$$

where $d_{\mathcal{D}_j}^O$ and $d_{\mathcal{D}_j}^L$ are disagreement points for the offloading and local computing services, respectively. According to (6), the solution of $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$ is obtained. In contrast to the $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$, the $\mathbb{G}_{\mathcal{D}_j}^{\Gamma}$ and $\mathbb{G}_{\mathcal{D}_j}^{\Theta}$ games are operated in the ε_i . Through these two games, the ε_i distributes its Γ_{ε_i} and Θ_{ε_i} for the $\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}$. First, the $\mathbb{G}_{\mathcal{D}_j}^{\Gamma}$ game determines the $\Gamma_{\varepsilon_i}^{\mathcal{D}_j}$ value by considering each individual device's condition. As a game player, the utility function of \mathcal{D}_j ($\mathcal{U}_{\mathcal{D}_j}(\cdot)$) is defined as follows:

$$\begin{aligned} & \mathcal{U}_{\mathcal{D}_j} \left(\Gamma_{\varepsilon_i}, \mathbb{D}_{\varepsilon_i}, \Upsilon_{\mathcal{D}_j}^{\varepsilon_i}, \Gamma_{\varepsilon_i}^{\mathcal{D}_j} \right) \\ &= \left[\frac{\exp \left(\frac{\min \left(\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}, \Gamma_{\varepsilon_i}^{\mathcal{D}_j} \right)}{\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}} \right) - \exp \left(-\frac{\min \left(\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}, \Gamma_{\varepsilon_i}^{\mathcal{D}_j} \right)}{\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}} \right)}{\exp \left(\frac{\min \left(\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}, \Gamma_{\varepsilon_i}^{\mathcal{D}_j} \right)}{\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}} \right) + \exp \left(-\frac{\min \left(\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}, \Gamma_{\varepsilon_i}^{\mathcal{D}_j} \right)}{\Upsilon_{\mathcal{D}_j}^{\varepsilon_i}} \right)} \right] \\ & \quad \times \Gamma_{\varepsilon_i}^{\mathcal{D}_j} \\ & \text{s.t., } \mathcal{D}_j \in \mathbb{D}_{\varepsilon_i} \text{ and } \Gamma_{\varepsilon_i} \geq \sum_{\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}} \Gamma_{\varepsilon_i}^{\mathcal{D}_j} \quad (7) \end{aligned}$$

where $\Gamma_{\varepsilon_i}^{\mathcal{D}_j}$ is the allocated computational power for the \mathcal{D}_j . In the $\mathbb{G}_{\mathcal{D}_j}^{\Gamma}$, all game players are devices in $\mathbb{D}_{\varepsilon_i}$, and they share the limited Γ_{ε_i} resource. From the viewpoint of game players, decreasing the difference in players' requirements for the Γ_{ε_i} needs the independence of alternatives other than the disagreement point. It states that the solution of a bargaining problem does not change as the set of feasible outcomes is reduced, so long as the disagreement point remains unchanged, and the solution originally selected remains feasible. This condition states that the selection of a feasible solution in an outcome set does not depend on any point except possibly the disagreement point [14]. In this case, *NBS* is preferred. Otherwise, *UBS* is suitable. As a decision control parameter, the ε value is dynamically adjusted based on the current difference ratio of $\Upsilon_{\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}}^{\varepsilon_i}$ and the solution of $\mathbb{G}_{\mathcal{D}_j}^{\Gamma}$ is given by:

$$\begin{aligned} & UF \left(\mathbb{D}_{\varepsilon_i}, \mathcal{U}_{\mathcal{D}_j}(\cdot), d_{\mathcal{D}_j}^{\Gamma} \mid \varepsilon \right) = \left[\sum_{\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}} \left(\mathcal{U}_{\mathcal{D}_j}(\cdot) - d_{\mathcal{D}_j}^{\Gamma} \right)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \\ & \text{s.t., } \varepsilon = \frac{\min_{\mathcal{D}_k, \mathcal{D}_h \in \mathbb{D}_{\varepsilon_i}} \left(\left| \Upsilon_{\mathcal{D}_k}^{\varepsilon_i} - \Upsilon_{\mathcal{D}_h}^{\varepsilon_i} \right| \right)}{\max_{\mathcal{D}_k, \mathcal{D}_h \in \mathbb{D}_{\varepsilon_i}} \left(\left| \Upsilon_{\mathcal{D}_k}^{\varepsilon_i} - \Upsilon_{\mathcal{D}_h}^{\varepsilon_i} \right| \right)} \quad (8) \end{aligned}$$

where $d_{\mathcal{D}_j}^{\Gamma}$ is the disagreement point of \mathcal{D}_j in the $\mathbb{G}_{\mathcal{D}_j}^{\Gamma}$. According to (8), the solution of $\mathbb{G}_{\mathcal{D}_j}^{\Gamma}$ is given. Second, the $\mathbb{G}_{\mathcal{D}_j}^{\Theta}$ game determines the $\Theta_{\varepsilon_i}^{\mathcal{D}_j}$ value to distribute the limited Θ_{ε_i} resource. Such as the $\mathbb{G}_{\mathcal{D}_j}^{\Gamma}$, the $\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}$ is a game player, and its utility function ($\mathcal{U}_{\mathcal{D}_j}(\cdot)$) is defined as follows:

$$\begin{aligned} & \mathcal{U}_{\mathcal{D}_j} \left(\mathbb{D}_{\varepsilon_i}, \Theta_{\varepsilon_i}, \Theta_{\varepsilon_i}^{\mathcal{D}_j}, \Theta_M^{\mathcal{D}_j} \right) = \frac{\log \left(\psi + \frac{\min \left(\Theta_{\varepsilon_i}^{\mathcal{D}_j}, \Theta_M^{\mathcal{D}_j} \right)}{\Theta_M^{\mathcal{D}_j}} \right)}{\log \left(\psi + \frac{\Delta}{\Theta_M^{\mathcal{D}_j}} \right)} \\ & \quad \times \Theta_{\varepsilon_i}^{\mathcal{D}_j} \\ & \text{s.t., } \mathcal{D}_j \in \mathbb{D}_{\varepsilon_i} \text{ and } \Theta_{\varepsilon_i} \geq \sum_{\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}} \Theta_{\varepsilon_i}^{\mathcal{D}_j} \quad (9) \end{aligned}$$

where ψ and Δ are adjustment factors for $\mathcal{U}_{\mathcal{D}_j}(\cdot)$, and $\Theta_M^{\mathcal{D}_j}$ is the \mathcal{D}_j 's maximum requirement for the Θ_{ε_i} . In the $\mathbb{G}_{\mathcal{D}_j}^{\Theta}$, all game players are devices in $\mathbb{D}_{\varepsilon_i}$, and they share the limited Θ_{ε_i} resource for wireless communications. The solution of $\mathbb{G}_{\mathcal{D}_j}^{\Theta}$ is obtained using the same concept as the solution of $\mathbb{G}_{\mathcal{D}_j}^{\Gamma}$. Therefore, it is given by:

$$\begin{aligned} & UF \left(\mathbb{D}_{\varepsilon_i}, \mathcal{U}_{\mathcal{D}_j}(\cdot), d_{\mathcal{D}_j}^{\Theta} \mid \varepsilon \right) = \left[\sum_{\mathcal{D}_j \in \mathbb{D}_{\varepsilon_i}} \left(\mathcal{U}_{\mathcal{D}_j}(\cdot) - d_{\mathcal{D}_j}^{\Theta} \right)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \\ & \text{s.t., } \varepsilon = \frac{\min_{\mathcal{D}_k, \mathcal{D}_h \in \mathbb{D}_{\varepsilon_i}} \left(\left| \Theta_M^{\mathcal{D}_k} - \Theta_M^{\mathcal{D}_h} \right| \right)}{\max_{\mathcal{D}_k, \mathcal{D}_h \in \mathbb{D}_{\varepsilon_i}} \left(\left| \Theta_M^{\mathcal{D}_k} - \Theta_M^{\mathcal{D}_h} \right| \right)} \quad (10) \end{aligned}$$

where $d_{\mathcal{D}_j}^{\Theta}$ is the disagreement point of \mathcal{D}_j in the $\mathbb{G}_{\mathcal{D}_j}^{\Theta}$. Using Eq. (10), the solution for $\mathbb{G}_{\mathcal{D}_j}^{\Theta}$ is determined.

D. MAIN STEPS OF OUR PEC RESOURCE ALLOCATION ALGORITHM

In this article, we propose a novel resource allocation algorithm to characterize the PEC platform while ensuring different VR applications. There are two types of resources of interest in this article: i) computing power and ii) wireless bandwidth. Because edge servers and devices are aware of their available resources, they are capable of discovering the best solution to balance the system performance. According to the idea of *UniBS*, we propose three different bargaining games, i.e., $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$, $\mathbb{G}_{\mathcal{D}_j}^{\Gamma}$ and $\mathbb{G}_{\mathcal{D}_j}^{\Theta}$, to address the resource sharing problems in a PEC infrastructure. Based on the fundamental concepts of *NBS*, *EBS* and *UBS*, a fair-efficient solution is dynamically selected to adapt to the current PEC system conditions. During discrete time periods, the $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$, $\mathbb{G}_{\mathcal{D}_j}^{\Gamma}$ and $\mathbb{G}_{\mathcal{D}_j}^{\Theta}$ games are operated repeatedly in a step-by-step interactive online manner. Owing to the desirable characteristics of *UniBS*, we can maximize the PEC system throughput,

TABLE 1. System parameters used in the simulation experiments.

Parameter	Value	Description
n	10	the total number of PEC servers
m	100	the total number of IoT devices
η	1	a control parameter for $U_D^L(\cdot)$
ψ, Δ	$1, \theta_M^D$	adjustment factors for $\mathcal{U}_D(\cdot)$
BOU	20 KHz	the basic unit for offload computing services
BBU	4 Mbps	the minimum amount of bandwidth allocation
θ_ε	2 Tbp	total communication capacity of each ε
Γ_ε	20 GHz	total computation power of each ε
\mathfrak{M}_D	1.5 GHz	total computing capacity of \mathcal{D}

VR task service types	Computation requirement(θ_M^D)	Computation requirement(γ_D)	Service duration
I	156 Mbps	240 KHz	20 t
II	64 Mbps	1.28 MHz	25 t
III	32 Mbps	780 KHz	30 t
IV	128 Mbps	320 KHz	35 t
V	48 Mbps	160 KHz	40 t
VI	256 Mbps	640 KHz	15 t

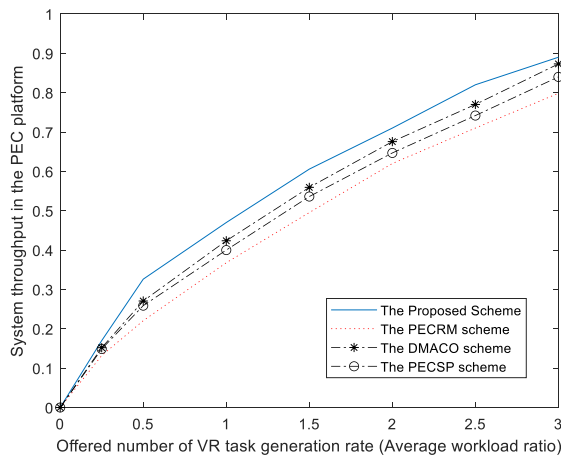


FIGURE 1. The PEC system throughput.

normalized device payoff and fairness while effectively satisfying contradictory requirements.

In this study, we do not focus on trying to get an optimal solution based on the traditional optimal approach. Instead, the decision mechanism in our interactive bargaining model is implemented with a polynomial complexity. From the viewpoint of practicality, this is a suitable approach for real-world system operations. The main steps of our proposed algorithm are as follows:

Step 1: To implement task offloading services in a PEC infrastructure, the values of the adjustment parameters and control factors are listed in Table 1, and the simulation testbed is presented in Section IV.

Step 2: At each time epoch, multiple devices generate their VR computing tasks in the IoT paradigm.

Step 3: From each individual $\mathcal{D}_{1 \leq j \leq m}$, the $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$ game is operated in a dispersive manner while contacting its corresponding ε_i . According to (5), the utility functions, i.e., $U_{\mathcal{D}_j}^O(\cdot)$ and $U_{\mathcal{D}_j}^L(\cdot)$, are defined.

Step 4: Based on the concept of *UniBS*, the solution of $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$ game is determined using (6).

Step 5: For each individual ε_i , the $\mathbb{G}_{\varepsilon_i}^\Gamma$ and $\mathbb{G}_{\varepsilon_i}^\Theta$ games are operated in a decentralized and parallel manner. In the $\mathbb{G}_{\varepsilon_i}^\Gamma$ game, the \mathcal{D}_j 's utility function, that is, $\mathcal{U}_{\mathcal{D}_j}(\cdot)$, is defined according to (7).

Step 6: Using (8), the solution of $\mathbb{G}_{\varepsilon_i}^\Gamma$ game is obtained while dynamically adjusting the ε value.

Step 7: In the $\mathbb{G}_{\varepsilon_i}^\Theta$ game, the \mathcal{D}_j 's utility function, i.e., $\mathcal{U}_{\mathcal{D}_j}(\cdot)$, is defined according to (9). Based on Eq.(10), the solution of $\Theta_{\varepsilon_i}^{\mathcal{D}_j}$ game is obtained.

Step 8: During discrete time periods, the sequential interactions of $\mathbb{G}_{\mathcal{D}_j}^{\varepsilon_i}$, $\mathbb{G}_{\varepsilon_i}^\Gamma$ and $\mathbb{G}_{\varepsilon_i}^\Theta$ games are explored to achieve mutual advantages. They work together to achieve an optimal PEC performance in a coordinated manner.

Step 9: Individual game entities constantly self-monitor the current system environments, and proceed to Step 2 for the next game process.

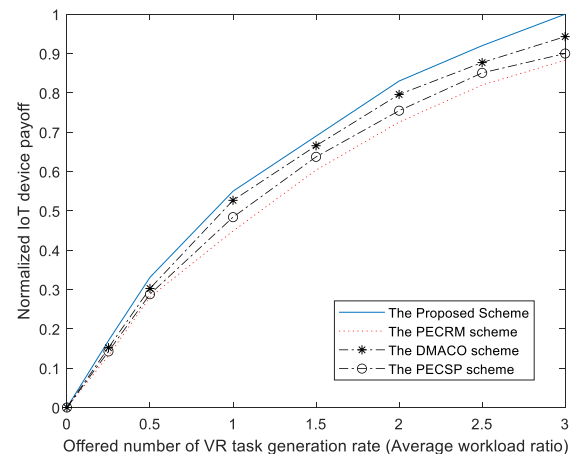


FIGURE 2. Normalized IoT device payoff.

IV. PERFORMANCE EVALUATION

In this section, we describe the simulation experiments conducted and analyze the performance of the proposed algorithm. The proposed algorithm is compared with other existing methods such as *PECRM*, *DMACO* and *PECSP* protocols in [5], [7], [12]. For performance comparison, we introduce the simulation scenario and specific experimental testbed as follows:

- The simulated PEC platform consists of ten edge servers, and 100 IoT devices where $|\mathbb{E}| = 10$ and $|\mathbb{D}| = 100$. The devices are located in the area neighboring of their corresponding servers.
- The total communication capacity (Θ_ε) of each ε is 2 Tbps, and the total computational power (Γ_ε) is 20 GHz.

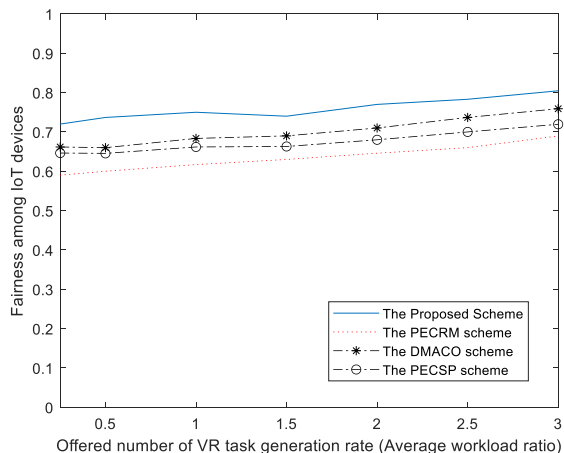


FIGURE 3. Access fairness of among IoT devices.

- The total computing capacity of $\mathcal{D}_j (\mathcal{M}_{\mathcal{D}_j})$ is 1.5 GHz.
- The disagreement point ($d_{\mathcal{D}}$) of each bargaining game is assumed to be zero.
- To reduce computational complexity, the amount of computation offloading process is specified in terms of basic offloading units (BOUs), where one BOU is the minimum amount (e.g., 20 kHz in our system) of computing offloading service. The amount of bandwidth allocation is also specified in terms of basic bandwidth units (BBUs), where one BBU is the minimum amount of bandwidth allocation (e.g., 4 Mbps in our system).
- VR computation tasks are generated for each individual IoT device. At each time epoch, the generation process for task services is Poisson with rate Λ (services/ t), and the range of offered workload was varied from 0 to 3.0.
- Six different VR task services are assumed based on their communication and computation requirements, and service duration times.
- The system performance measures obtained basis on 100 simulation runs are plotted as a function of the task request workload.

Fig. 1 depicts the average system throughput as a function of the increasing workload rate, for different PEC task offloading protocols. In our simulation model, system throughput is defined as the ratio of successfully serviced tasks to all generated tasks. From the simulation results, we observe that as the workload rate increases, the system throughput also increases. In particular, it can be seen that the throughput of our proposed scheme is higher than that of the other existing schemes from low to heavy workload intensities. This outcome confirms that our bargaining game approach can make control decisions adaptively under the dynamics of PEC platform environments, leading to optimized system performance.

Fig. 2 shows the normalized payoff received by the devices of all protocols. As shown in Fig. 1, the proposed scheme maintains higher payoff outcomes for different task workload situations. When the workload load increases, it becomes

more certain. This is because of the pure benefits stemming from the optimization of the partial offloading process. In the proposed scheme, individual IoT devices can handle all their computation tasks by taking advantage of *UniBS* for offloading services. The simulation results clearly indicate that efficient properties can be guaranteed in the resource allocation problem of the PEC platform.

The fairness comparisons among the devices on the PEC platform are plotted in Fig. 3. We can see from the figure that our proposed scheme can achieve the best fairness compared with the *PECRM*, *DMACO* and *PECSP* protocols for the range of offered workload rates. Traditionally, cooperative games and bargaining solutions have been paradigmatic for certain fairness considerations. The major characteristic of *UniBS* is that it provides a fair-efficient solution while ensuring the tradeoff between *NBS*, *EBS* and *UBS*. This leads to a preferable outcome in the fairness comparison. The simulation results shown in Figs. 1-3 demonstrate that the proposed scheme can strike an appropriate performance balance under widely diversified task workload intensities in the PEC infrastructure.

V. SUMMARY AND CONCLUSION

In this study, we investigate the computation and communication resource allocation problems of the PEC platform. To address these problems efficiently, we study a suitable unification solution concept by considering different bargaining ideas while adapting to dynamically changing PEC system conditions. Based on *UniBS*, the $\mathbb{G}_{\mathcal{D}}^{\epsilon}$, $\mathbb{G}_{\epsilon}^{\Gamma}$ and $\mathbb{G}_{\epsilon}^{\Theta}$ games are formulated to achieve the goal of maximizing the system performance. Then, these games work together interactively in a step-by-step cooperative manner to select their optimal strategies in an online fashion. Finally, extensive experimental simulations are performed to prove the effectiveness of our proposed approach. The numerical results show that the proposed bargaining approach outperforms the existing *PECRM*, *DMACO* and *PECSP* protocols in terms of system throughput, device payoff and fairness. So, in sum, it is worth noting that the *UniBS* based $\mathbb{G}_{\mathcal{D}}^{\epsilon}$, $\mathbb{G}_{\epsilon}^{\Gamma}$ and $\mathbb{G}_{\epsilon}^{\Theta}$ games can efficiently utilize the limited computational and communication resources in the PEC system platform.

Our future work will involve conducting experiments to test the validity and performance of our proposed method on a real PEC platform. Furthermore, as there are still potentials in each decision making part of our coexisting bargaining games, we aim to integrate security, AI, and edge computing to enhance the performance of IoT-enabled PEC. In addition, to protect low-powered IoT devices from Sybil attacks, we propose a lightweight Sybil attack-detection protocol. In the direction of this approach, we will devote attention to security problems, including man-in-the-middle attacks, DoS attacks, and DDoS attacks that threaten the IoT infrastructure.

COMPETING OF INTERESTS

The author declares that there are no competing interests regarding the publication of this paper.

AUTHOR CONTRIBUTION

The author is a sole author of this work and ES (i.e., participated in the design of the study and performed the statistical analysis).

AVAILABILITY OF DATA AND MATERIAL

The data used to support the findings of this study are available by contacting the corresponding author at swkim01@sogang.ac.kr.

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