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Research Article

Novel Resource Allocation Algorithms for the Social Internet of Things Based Fog Computing Paradigm

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Social Internet of Things (SIoT) is a control paradigm by the integration of social networking concepts into the Internet of Things, and Fog Computing (FC) is an emerging technology that is aimed at moving the cloud computing facilities to the access network. Recently, the SIoT and FC models are combined by using complementary features, and a new Social Fog IoT (SFIoT) paradigm has been developed. In this paper, we design novel resource allocation algorithms for the SFIoT system. Considering the social relationship and each preference, mobile devices in the SFIoT effectively share the limited computation and communication resources of FC operators. To formulate the interaction among mobile devices and FC operator, we adopt the basic concept of two game models: voting and bargaining games. Bicooperative voting approach can make control decisions for the resource allocation method, and Nash bargaining solution is used to effectively distribute the computation resource to different application tasks. Based on the two-phase game model, the proposed scheme takes various benefits in a fair-efficient way. Through the extensive simulation experiments, we can validate the superiority of our proposed approach by the fact that it produces a mutually acceptable agreement among game players and significantly outperforms the existing protocols. Last, we point out the further challenges and future research issues about the SFIoT paradigm opportunities.

1. Introduction

Since its birth in the early 1960s, the Internet has made enormous progress in research, development, and innovation in the data communications. Recently, the Internet has started to connect every *thing* in the physical world. This pervasive paradigm known as Internet of Things (IoT) might increase the value of information exchanged by the number of interconnected things and can usher in a wide range of smart services and applications for the benefit of mankind and society. Accordingly, the IoT technologies make it possible to provide new services to end-users while establishing social relationships in an autonomous way. Similar to what happens with social networks among humans, smart objects in the IoT connected each other asymmetrically with their preference similarity and interests [1–3].

The integration of social networking concepts into the IoT has led to a burgeoning topic of research, the so-called Social IoT (SIoT) paradigm. In the SIoT, smart objects can find the desired services through its social networking in a decentralized manner. The term 'social networking' revolves around not only the online social networking, but also the natural social relations in the local area. Therefore, the inter-thing social network can be exploited based on social device-to-device short-range wireless connections. As a consequence, we have witnessed the rise of tremendous business and social opportunities in the SIoT paradigm. The SIoT paradigm effectively addresses the scalability issue of the native IoT paradigm by enforcing the convergence of social and communication networks. However, the social connectivity-based IoT services may cause the cascade effect. Therefore, for effective and efficient SIoT operations, the main objective pursued by the SIoT paradigm is to maximize the social welfare based on the social relations [2, 4].

In the era of big date based computation-intensive applications, data generated from SIoT devices are generally processed in a cloud infrastructure. However, it may be inefficient to send the large data of IoT devices to the remote cloud system, especially for time-sensitive applications. To address this issue, Fog Computing (FC) method has exhibited the right features. FC provides low-latency computing cloud services at the edge of the network where data is generated. To implement the FC architecture, edge agents are evolved to the edge clouds, called cloudlets, by being equipped with a certain computation power capability. Therefore, it is an enabler for the emerging SIoT systems while handling the rapid development of computation-intensive applications. Compared to the traditional cloud computing, the FC method with SIoT system can greatly improve the efficiency by providing the powerful computing resource through one-hop wireless connections [5, 6].

Usually, SIoT and FC are two stand-alone technological paradigms under the realm of the future generation networks. To guarantee the scalability of large IoT, SIoT relies on the self-establishment and self-management of inter-thing social relationships. To support the computation-intensive applications in IoT devices, FC extends cloud capabilities to the edges of access networks. Motivated by these complementary features of the SIoT and FC methods, a new paradigm, called Social Fog IoT (SFIoT), has been introduced by integrating the SIoT and FC technologies. The main idea behind the SFIoT paradigm is to embrace the design principles related to both SIoT and FC methods [4].

In the SFIoT system, each cloudlet is a small-size virtualized inter-connected resource-equipped data center. At the edge of access networks, the cloudlet hosts the thing-to-FC offloading tasks for SFIoT devices. By using the intra-FC resource pooling technique, each cloudlet partitions the available resource for each application type [4]. In the SFIoT system, there are two types of resources: computation and communication. However, whereas, in reality, the computation and communication resources of each individual cloudlet are limited and raced. When a lot of computation-intensive applications are offloaded, the resources of cloudlet will become exhausted rapidly and the quality of experience (QoE) will be seriously degraded [7–9]. To allocate limited computation and communication resources to SFIoT services, efficient resource allocation is a critical issue in order to improve the total system performance while ensuring the QoE provisioning. In this study, we are solving the cloudlet's resource allocation problem for SIoT devices, which are connected according to interdevice social ties [10].

The past decade has witnessed a huge explosion of interest in game theory. As a branch of Applied Mathematics, game theory is concerned with decision-making in strategic settings, and it has been successfully applied to tackle many distributed selfish optimization problems. Game theory can be divided into noncooperative game and cooperative game. If game players can reach a binding agreement, then the game becomes a cooperative game. On the contrary, this agreement cannot be reached in the noncooperative game. In particular, cooperative game theory can be used to analyze many distributed selfish optimization problems in communication networks [11].

In the SFIoT vision, individual devices interact according to the peer-to-peer communication model by autonomously building up inter-thing social relationships with respect to their preferences [4]. To improve the total SFIoT system performance, each individual device needs to cooperate with each other. To get the mutual advantages for themselves, the relationship of interrelated SFIoT devices can be modeled as cooperative games. Inspired by the basic concept of cooperative games, the major question to be answered is how to reach a consensus for the effective SFIoT resource allocation. This issue is our main concern in this study.

In 1950s, John Nash proposed a simple cooperative game model, which predicted an outcome of bargaining based only on information about each player's preferences. To allocate resources fairly and optimally, Nash Bargaining Solution (NBS) is the unique bargaining solution that satisfies six axioms: *individual rationality*, *feasibility*, *symmetry*, *pareto optimality, independence of irrelevant alternatives*, and *invariance with respect to utility transformations*. Therefore, it can achieve a mutually desirable solution with a good balance between efficiency and fairness. In addition, the NBS does not require global objective functions, unlike conventional optimization methods, such as Lagrangian or dynamic programming [11].

As a kind of cooperative game, simple voting game is very useful in modeling a decision-making process. However, it allows each voter only two choices: to support or oppose a decision. This restriction ignores that voters often can abstain from voting, which is effectively different from the other two options [12, 13]. By considering abstainers, Bicooperative Voting Game (BVG) can formulate a more realistic decision-making process to adaptively control the SFIoT system.

Based on these appealing properties, we adopt the basic concepts of NBS and BVG to solve the resource allocation problem in the SFIoT system. For the computation resource allocation, we adopt the NBS. It is formulated by an expected utility function over the set of feasible agreements based only on information about each player's preferences. For the communication resource allocation, we use the fundamental idea of voting game. However, classical voting games cannot be effectively applied to design our SFIoT resource allocation algorithm. As a special class of voting games, the BVG can formulate a more realistic decision-making process to adaptively allocate the communication resource of the SFIoT system. With desired properties of NBS and BVG, we attempt to reach an outcome that meets our design goals while taking reciprocal advantages in a technologically more suitable way.

1.1. Related Work. Due to the driving force for the improvement of SFIoT system, there have been considerable researches about the implementation of social relation based FC control algorithms, and some SFIoT control schemes have been published. L. Liu et al. propose the *socially aware dynamic fog computing* (*SDFC*) scheme for the computation offloading mechanism [14]. This scheme advocates a game theoretic model and proposes a new dynamic computation offloading method to minimize the social group execution cost. In particular, a computation offloading problem in a FC system has been investigated and this problem is formulated as a generalized Nash equilibrium problem. To derive the delay performance during the offloading process, different queue models are also applied. Finally, it is addressed by using the semi-smooth Newton method with Armijo line search. The *SDFC* scheme can reduce the accumulated error and adaptively improves the calculation accuracy during iteration process. The simulation results demonstrate the effectiveness of the *SDFC* scheme [14].

The *social system through edge computing* (*SSEC*) scheme is proposed as a new collaborative, horizontal offloading method for the distributed data processing mechanism [15]. To discover and select devices, which are able to perform an offloaded task according to specific requirements, this scheme implements the clustered edge computing paradigm. Currently, personal mobile devices are seen not only as passive data generators and IoT service consumers, but rather as active participants and contributors. Based on the principles of volunteer computing and SIoT, the *SSEC* scheme presents a novel approach to address network latency issues at the very edge of an IoT network topology while utilizing idle resources of mobile devices. Finally, the simulation results show that the *SSEC* scheme has a potential power to outperform cloud-centric setups by keeping the computation locally and by involving volunteering mobile devices in clustered computation at the edge [15].

Paper [16] presents the *cloud-fog information-centric computing* (*CFIC*) scheme. This scheme supports IoT applications in various network domains with the IoT middleware and the cloud-fog computing mechanism. By using two functions, i.e., job-classification function and resource scheduling function, QoE in IoT applications can be ensured. Specifically, the job-classification function classifies different IoT applications by authority, data type, data update rate, and priority. The resource scheduling function generates a resource allocation plan based on the resource limitation. Simulation results reveal that the *CFIC* scheme can reduce the cloud computing time while guaranteeing the execution of real-time IoT applications [16].

The earlier studies [14–16] have attracted considerable attentions while introducing unique challenges in handling the SFIoT resource allocation problem. Therefore, our proposed scheme may look similar to the existing schemes. While these schemes have some similarities, there are several key differences. First, our proposed scheme is designed as a two-phase game model based on the two different cooperative game approaches. Second, in our game model, the main concepts of NBS and BVG are adopted to address the SFIoT resource allocation problem. Third, to reduce the computation complexity, we hierarchically implement the BVG and the NBS with cascade interactions. Most of all, the main difference between the existing schemes in [14–16] and our proposed scheme is a control paradigm. The principle novelty of our protocol is a judicious mixture of two game solutions, and its feasible self-adaptability in the real-world SFIoT system operations. In this paper, we compare our proposed scheme with the existing the *SDFC* [14], *SSEC* [15], and *CFIC* [16] schemes and demonstrate that our two-phase interactive game approach can significantly outperform these existing schemes.

The main contributions of this study are (i) ability to maintain the SFIoT resource efficiency as high as possible, (ii) ability to respond to current SFIoT situations based on the interactive bargaining and voting process, (iii) QoE provisioning for different kinds of application tasks, (iv) synergy effect based on the reciprocal combination of SIoT and FC, and (v) ensuring a mutually desirable solution while improving the overall SFIoT system performance. The key advantage of the proposed scheme is its adaptability, feasibility, and effectiveness for realistic SFIoT system operations under widely different and diversified application task load situations.

The rest of this paper is organized as follows. Section 2 presents the SFIoT system infrastructure and the background knowledge of NBS and BVG concepts. And then, the details of our proposed scheme are explained based on the interactive two-phase game model. In Section 3, we provide the numerical results from simulation experiments, and demonstrate the effectiveness of the proposed scheme comparing with the existing *SDFC* [14], *SSEC* [15], and *CFIC* [16] protocols. Finally, conclusions and suggestions for future research are given in Section 4.

2. The Proposed SFIoT Resource Allocation Algorithms

In this section, we describe a new two-phase game approach for solving the resource allocation problem of SFIoT system. In the first phase, mobile devices take two votes to decide communication and computation resource allocation ways. In the second phase, the computation capacity is distributed to each application task based on the NBS. Finally, we explain in detail the proposed scheme in the nine-step procedures.

2.1. Fog Controlled Social IoT System Infrastructure. Traditionally, the SFIoT system infrastructure is consisting of multiple cloudlets and a number of mobile devices. As a small-scale cloud datacenter, each cloudlet is located at the edge of the Internet. The main purpose of the cloudlet is supporting resource-intensive and interactive mobile applications by providing powerful computing resources with lower latency. In the SFIoT system, each individual mobile device is a member of both an underlying IoT and an overlay social network. Usually, the IoT accounts for more conventional network services, and the social network reflects somewhat less conventional social ties induced by inter-thing social relationships, which are formally described by a social graph $\mathbb{G} = (\mathbb{N}, \mathbb{E})$; $\mathbb{N}$ is the set of mobile devices and $\mathbb{E} = \{e_{m_i,m_j} \mid 0 \le e_{m_i,m_j} \le 1$ and $(m_i, m_j) \in \mathbb{N} \times \mathbb{N}\}$ is the set of the social ties. e_{m_i,m_j} is a real-valued nonnegative number to measure the strength of the social tie between m_i and m_j. Therefore, $\mathbb{S}_{m_i} = \{m_j \mid e_{m_i,m_j} > 0$ and $m_j \in \mathbb{N}\}$ formally defines the set of the social friends of m_i [4].

To calculate each user's influential power, we develop a social power function $\mathcal{F}(x)$, in line with some properties. Under diverse scenarios, the function $\mathcal{F}(x)$ should obey the following three properties to effectively estimate each individual user's social power [17].

(i) *nonnegative property*: $\mathcal{F}(x) \geq 0$,

(ii) *nondecreasing property*: $d\mathcal{F}(x)/dx \geq 0$,

(iii) *saturation property*: $d^2\mathcal{F}(x)/dx^2 < 0$

The *nonnegative* property means that the outcome should be larger than zero, and if there is no social relationship, it is zero. The *nondecreasing* property simply implies that the more users are socially connected, the more outcome can be obtained. The *saturation* property suggests that when the social relationship is sufficient, any further increase of the outcome remains marginal [17]. In order to construct a function while satisfying above three properties, the social power function of m_i, i.e., $\mathcal{F}_{m_i}(x)$, is defined as follows:

$$\mathcal{F}_{m_i}(x) = \Gamma - \frac{1}{\exp(\mu \times x)}, \quad \text{s.t.,} \quad x = \sum_{m_j \in \mathbb{S}_{m_i}} e_{m_i,m_j} \tag{1}$$

where μ controls the speed of social power saturation and Γ represents the maximum outcome of a user to normalize the social power [17].

In this study, we assume that there are k cloudlets and n mobile devices where $k \ll n$. In the SFIoT system infrastructure, cloudlets are evolved to the Fog-computing based Access Point (F-AP) by being equipped with a certain computation power and communication capability. The design of F-AP platform has been introduced to deliver various devices requests, which have different characteristics and resource demands, that is, CPU capacity for computation and wireless bandwidth assignment for communication. However, due to the limited CPU capacity and bandwidth scarcity in the F-AP, it is impossible to guarantee all applications' needs [18]. Therefore, an efficient resource management strategy becomes a key factor in enhancing the SFIoT performance while ensuring the required QoE.

To tackle the SFIoT resource control problem, we propose a two-phase game based resource allocation scheme. At the first phase, individual mobile devices participate in two BVGs; one is to decide the allocation method of communication resource, and the other is to partition the computation resource according to the voting power of each mobile device. In each F-AP covering area, the voting power is calculated based on the pseudo-Banzhaf value. At the second phase, the partitioned computation capacity is distributed for same kinds of application tasks based on the NBS. To practically implement our resource allocation algorithms, each individual F-AP and its corresponding mobile devices operate their own two-phase game in an entirely distributed manner. For example, the k^{th} F-AP, i.e., $\mathcal{F}_k^{AP}$, and the set of corresponding mobile devices in $\mathcal{F}_k^{AP}$'s covering area, i.e., $\mathbb{N}_{\mathcal{F}_k^{AP}}$, work together for their two-phase game $\mathbb{G}_k$. Therefore, multiple two-phase games $\mathbb{G}_{1\leq i\leq k}$ are operated in parallel. To formally define our proposed game model, we characterize $\mathbb{G}_k$ as $\{\{\mathcal{F}_k^{AP}, \mathbb{N}_{\mathcal{F}_k^{AP}}\}, \{(\mathbb{S}_{m_i}, \mathcal{F}_{m_i}(x), \Psi_{m_i}^{\mathcal{Q}}) \mid m_i \in \mathbb{N}_{\mathcal{F}_k^{AP}},\ x = \sum_{m_j \in \mathbb{S}_{m_i}} e_{m_i,m_j}\}, \mathbb{A}_{\mathcal{F}_k^{AP}}, \alpha_{\mathcal{F}_k^{AP}}, U_{\mathcal{F}_k^{AP}}\}$. Table 1 lists the notations used in this paper.

(i) $\{\mathcal{F}_k^{AP}, \mathbb{N}_{\mathcal{F}_k^{AP}}\}$ is the set of game players for the $\mathbb{G}_k$ game where $\mathbb{N}_{\mathcal{F}_k^{AP}} \cap \mathbb{N}_{\mathcal{F}_l^{AP}} = \emptyset$.

(ii) $(\mathbb{S}_{m_i}, \mathcal{F}_{m_i}(x), \Psi_{m_i}^{\mathcal{Q}})$ is a three-pair for the $m_i \in \mathbb{N}_{\mathcal{F}_k^{AP}}$, where $\mathbb{S}_{m_i}$ is the set of m_i's social friends. $\mathcal{F}_{m_i}(x)$ and $\Psi_{m_i}^{\mathcal{Q}}$ represent the social power and the voting power of m_i, respectively.

(iii) $\mathbb{A}_{\mathcal{F}_k^{AP}}$ is the set of generated application tasks, which are offloaded in the $\mathcal{F}_k^{AP}$ for FC services.

(iv) $\alpha_{\mathcal{F}_k^{AP}}$ is the ratio of relative service weights given to different type applications in the $\mathcal{F}_k^{AP}$ where $0 \leq \alpha_{\mathcal{F}_k^{AP}} \leq 1$. Based on the $\alpha_{\mathcal{F}_k^{AP}}$ value, $\mathcal{F}_k^{AP}$'s computation power is partitioned.

(v) $U_{\mathcal{F}_k^{AP}}$ is the utility function of $\mathcal{F}_k^{AP}$; it is optimized based on the NBS.

2.2. Bicooperative Game and Ternary Voting Model. Usually, cooperative game theory studies situations where a group of game players are associated to obtain a profit as a result of their cooperation. Thus, a cooperative game model is defined as a pair $(N, \mathcal{V})$, where N is a finite set of players and $\mathcal{V}$: $2^N \longrightarrow \mathbb{R}$ is a function verifying that $\mathcal{V}(\emptyset) = 0$. For each coalition $S \in 2^N$, $\mathcal{V}(S)$ can be interpreted as the coalition S's maximal gain that players in S can achieve themselves against the best offensive threat by the complementary coalition $N \setminus S$ [12].

In 2008, Bilbao et al. proposed a new idea, called bicooperative game for the multicriteria decision-making process. In the bicooperative game, game players are allowed to choose one among three alternatives. To think the voting situation by analogy, we consider ordered pairs (S, T), with $S, T \subseteq N$ and $S \cap T = \emptyset$. Each pair (S, T) yields a partition of N in three groups. Players in S are in favor of the voting item, and players in T object to it. The remaining players in $N \setminus (S \cup T)$ are nonvoters. Formally, we can define the set $3^N = \{(S,T) \mid S,T \subseteq N, S \cap T = \emptyset\}$ and the function $\mathcal{Q} : 3^N \longrightarrow \mathbb{R}$. For each $(S,T) \in 3^N$, the outcome of $\mathcal{Q}(S,T)$ can be interpreted as the gain that S can achieve when T is the opposite coalition and $N \setminus (S \cup T)$ is the neutral coalition [12, 13].

The pair $(\emptyset, N)$ represents the situation if all the players object to the voting item and $(N, \emptyset)$ represents the situation where all the players support the voting item. More generally, a relation of 3^N is given by [12, 13]

$$(A,B) \sqsubseteq (C,D) \Longleftrightarrow A \subseteq C,\ B \supseteq D \tag{2}$$

The set $(3^N, \sqsubseteq)$ is a finite distributive lattice and a partially ordered set with the following properties [12, 13]:

(i) $(\emptyset, N)$ is the first element: $(\emptyset, N) \sqsubseteq (A,B)$ for all $(A,B) \in 3^N$

(ii) $(N, \emptyset)$ is the last element: $(A,B) \sqsubseteq (N, \emptyset)$ for all $(A,B) \in 3^N$

Table 1: Symbols and parameters used in the proposed algorithm.

Notations	Explanation
$\mathbb{N}$	the set of mobile devices
$\mathbb{E}$	the set of the social ties
e_{m_i,m_j}	a real-valued number to measure the strength of the social tie between m_i and m_j
$\mathbb{S}_{m_i}$	the set of the social friendsof m_i
$\mathscr{F}_{m_i}(x)$	the social power function of m_i,
μ	a parameter to control the speed of social power saturation
Γ	the maximum outcome of a user to normalize the social power
$\mathscr{F}_k^{AP}$	the k^{th} fog-computing based access point
$\mathbb{N}_{\mathscr{F}_k^{AP}}$	the set of corresponding mobile devices in the $\mathscr{F}_k^{AP}$'s covering area
$\mathbb{G}_k$	The two-phase game in $\mathscr{F}_k^{AP}$
$\Psi_{m_i}^{\mathcal{Q}}$	the social power and the voting power of m_i
$\mathbb{A}_{\mathscr{F}_k^{AP}}$	the set of application tasks, which are offloaded in the $\mathscr{F}_k^{AP}$ for FC services
$\alpha_{\mathscr{F}_k^{AP}}$	the ratio of relative service weights given to different type applications in the $\mathscr{F}_k^{AP}$
$U_{\mathscr{F}_k^{AP}}$	the utility function of $\mathscr{F}_k^{AP}$
N	a finite set of voting game players
$\mathscr{V}(S)$	the coalition S's maximal gain
$\mathcal{Q}(S,T)$	the gain that S can achieve when T is the opposite coalition
$\mathscr{B}\mathscr{G}^N$	the set of all bicooperative games with players N
$\phi_i(\mathcal{Q})$	the player i's value in a game $\mathcal{Q}$ on $\mathscr{B}\mathscr{G}^N$
$\check{\mathcal{Q}}_{(S,T)}(A,B)$	the *identity* game
$\overline{\mathcal{Q}}_{(S,T)}(A,B)$	the *superior unanimity* game
$\underline{\mathcal{Q}}_{(S,T)}(A,B)$	the *inferior unanimity* game
$\mathcal{Q}_i$	the payoff of voter i
$\mathscr{W}(S)$	the sum of voting weights of coalition S's players
$\mathfrak{P}$	the quota for the decision-taking
ϑ	the quota for the decision-blocking
$\mathfrak{X}$	a weighted ternary voting game
$\mathfrak{B}$	the total available bandwidth amount
m_i	the pre-defined minimum bandwidth amount for the i^{th} service
R_i	the bandwidth request of mobile device m_i
A_i	the decided bandwidth amount for the m_i
T^C, $\mathscr{L}^C$	the constraint thresholds, which are chosen to satisfy each condition
α_I	the preference ratio of class I application services
$\mathscr{C}$	each F-AP's total computation capacity
η_I,η_{II}	control parameters to adjust the payoff of m
$\mathscr{C}_{\mathscr{F}_k^{AP}}$	the total computation capacity of $\mathscr{F}_k^{AP}$

(iii) Every fair of elements of 3^N has a join

$$(A,B)\bigvee(C,D)=(A\cup C,B\cap D)$$
$$\text{and}\quad (A,B)\wedge(C,D)=(A\cap C,B\cup D) \tag{3}$$

The set of all bicooperative games with players N is denoted by $\mathscr{B}\mathscr{G}^N$, which is a real vector space [12, 13].

$$\mathscr{B}\mathscr{G}^N=\left\{\mathcal{Q}\mid 3^N\longrightarrow\mathbb{R}\text{ and }\mathcal{Q}(\emptyset,\emptyset)=0\right\} \tag{4}$$

A value on $\mathscr{B}\mathscr{G}^N$ is a mapping $\phi:\mathscr{B}\mathscr{G}^N\longrightarrow\mathbb{R}^n$ that associates with each game $\mathcal{Q}\in\mathscr{B}\mathscr{G}^N$. In a vector $(\phi_1(\mathcal{Q}),\ldots,\phi_n(\mathcal{Q}))\in\mathbb{R}^n$, $\phi_{1\le i\le n}(\mathcal{Q})$ represents a real number, which is the player i's value in a game $\mathcal{Q}$ on $\mathscr{B}\mathscr{G}^N$. Therefore, the mapping $\phi_{i\in N}(\mathcal{Q}):\mathscr{B}\mathscr{G}^N\longrightarrow\mathbb{R}$ represents the player i's payoff from playing bicooperative games [12, 13]. There are three special collections of games in $\mathscr{B}\mathscr{G}^N$ taking values in $\{-1,0,1\}$: the *identity* games, the *superior unanimity* games, and the *inferior unanimity* games which are defined for any $(S,T)\in 3^N$ [12, 13].

The *identity* game $\{\check{\mathcal{Q}}_{(S,T)}(A,B)\mid 3^N\longrightarrow\mathbb{R}\}$ is defined by

$$\check{\mathcal{Q}}_{(S,T)}(A,B)$$

$$= \begin{cases} 1, & \text{if } (A,B) = (S,T) \text{ and } (S,T) \neq (\emptyset,\emptyset) \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The *superior unanimity* game $\{\overline{\mathcal{Q}}_{(S,T)}(A,B) \mid 3^N \longrightarrow \mathbb{R}\}$ is defined by

$$\overline{\mathcal{Q}}_{(S,T)}(A,B) = \begin{cases} 1, & \text{if } (S,T) \sqsubseteq (A,B) \text{ and } (A,B) \neq (\emptyset,\emptyset) \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

The *inferior unanimity* game $\{\underline{\mathcal{Q}}_{(S,T)}(A,B) \mid 3^N \longrightarrow \mathbb{R}\}$ is defined by

$$\underline{\mathcal{Q}}_{(S,T)}(A,B) = \begin{cases} -1, & \text{if } (A,B) \sqsubseteq (S,T) \text{ and } (A,B) \neq (\emptyset,\emptyset) \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Voting game is a cooperative game model that incorporates elements from social choice theory. This game model can be used to analyze situations where voters would vote in favor of or against a decision [11]. Simple voting game with abstention can be formulated as a bicooperative game. It has been studied under the name of ternary voting game [19, 20].

Let N be a set of n voters that has to choose between a pair of two alternatives S and T. Every voter $i \in N$ has a preference over the two alternatives S and T. Thus, the payoff of voter i ($\mathcal{Q}_i$) is defined by $\mathcal{Q}_i : 3^N \longrightarrow \{-1,0,1\}$ based on the majority rule. Formally, a ternary voting game $\mathcal{Q} \in \mathcal{BG}^N$ satisfies the following conditions [19].

(I) For every bicoalition pair $(S,T) \in 3^N$, its worth $\mathcal{Q}(S,T) \in \{-1,0,1\}$.

(II) If $(S,T), (\widehat{S},\widehat{T}) \in 3^N$ with $(S,T) \sqsubseteq (\widehat{S},\widehat{T})$, then $\mathcal{Q}(S,T) \leq \mathcal{Q}(\widehat{S},\widehat{T})$

(III)

$$\mathcal{Q}_i = \begin{cases} 1, & \text{if } (i \in S \text{ and } |S| > |T|) \text{ or } (i \in T \text{ and } |T| > |S|) \\ -1, & \text{if } (i \in S \text{ and } |S| < |T|) \text{ or } (i \in T \text{ and } |T| < |S|) \\ 0, & \text{if voter i abstains form voting or } |S| = |T| \end{cases} \tag{8}$$

where $|S|$ is the cardinality of coalition S. For voting games, the analysis of voting power is the main issue. In 1965, Banzhaf value was introduced by John F. Banzhaf III based on probabilistic analysis of the individual voters in a block voting system. It depends on the number of ways in which each voter can effect a swing in the game. In 2010, J. Bilbao et al. introduced a pseudo-Banzhaf value, i.e., $\Psi_i^{\mathcal{Q}}$, for the ternary voting game $\mathcal{Q}$; it can be interpreted as a voter's probabilistic power index [19, 20].

$$\Psi_i^{\mathcal{Q}} = \frac{1}{3^{n-1}} \times \sum_{(S,T) \in 3^{N \setminus i}} \left(\mathcal{Q}_i (S \cup \{i\}, T) - \mathcal{Q}_i (S, T \cup \{i\}) \right) \tag{9}$$

The pseudo-Banzhaf value satisfies four axioms; *Null Player*, *Total Swings*, *Transfer Property*, and *Simple Additivity* [19, 20].

Axiom 1 (null player). If $i \in N$ is a null player in $\mathcal{Q} \in \mathcal{BG}^N$, then $\Psi_i^{\mathcal{Q}} = 0$. Therefore, if the player i is the null player in $\mathcal{Q}$ with any $(S,T) \in 3^{N \setminus i}$, then

$$\begin{aligned} \mathcal{Q}_i (\{i\}, \emptyset) &= \left(\mathcal{Q}_i (S \cup \{i\}, T) - \mathcal{Q}_i (S,T) \right) \\ \mathcal{Q}_i (\emptyset, \{i\}) &= \left(\mathcal{Q}_i (S,T) - \mathcal{Q}_i (S, T \cup \{i\}) \right) \\ \phi_i (\mathcal{Q}) &= \left(\mathcal{Q}_{(S,T)} (\{i\}, \emptyset) - \mathcal{Q}_{(S,T)} (\emptyset, \{i\}) \right) \end{aligned} \tag{10}$$

Axiom 2 (total swings). If $\mathcal{Q} \in \mathcal{BG}^N$, then

$$\sum_{i \in N} \Psi_i^{\mathcal{Q}} = \sum_{(S,T) \in 3^{N \setminus i}} \left(\mathcal{Q}_i (S \cup \{i\}, T) - \mathcal{Q}_i (S, T \cup \{i\}) \right) \tag{11}$$

Axiom 3 (transfer property). For any $\mathcal{Q}, \mathcal{G} \in \mathcal{BG}^N$, we have that

$$\left(\phi_i (\mathcal{Q}) + \phi_i (\mathcal{G}) \right) = \left(\phi_i \left(\mathcal{Q} \bigvee \mathcal{G} \right) + \phi_i (\mathcal{Q} \wedge \mathcal{G}) \right) \tag{12}$$

Axiom 4 (simple additivity). For any $\mathcal{Q} \in \mathcal{BG}^N$ such that $\mathcal{Q} = \mathcal{G} + \mathcal{H}$, we have that

$$\phi_i (\mathcal{Q}) = \left(\phi_i (\mathcal{G}) + \phi_i (\mathcal{H}) \right) \tag{13}$$

As a special ternary voting game model, the weighted ternary voting game can formulate a decision-making process that not all voters have the same amount of influence over the decision. Therefore, votes of different voters are given different weight. This type of voting game model is used in shareholder meetings, where votes are weighted by the number of shares that each shareholder owns [11]. In this study, we develop a ternary voting game model based on the weighted voting approach. In our game model, mobile devices are treated differently according to their social powers ($\mathcal{F}_m(x)$) and give different amounts of influence to different members. Therefore, each coalition of players $S \subseteq N$ has the sum of voting weights of its components; that is, $\mathcal{W}(S) = \sum_{m_i \in S} \mathcal{F}_{m_i}(x)$. If the value of $\mathcal{W}(S)$ exceeds a certain quota, players in S win the game [11, 19].

For the weighted ternary voting game, we need two quotas; one is to block a decision, and the other is to approve it. Formally, it is represented by the voting body $[\mathfrak{P}, \vartheta; \mathcal{F}_{m_1}(x), \ldots \mathcal{F}_{m_n}(x)]$ where $\mathfrak{P}$ is the quota for the decision-taking and ϑ is the quota for the decision-blocking; it can be seen as a particular case of n-player games with three choices. This situation can be formulated by a weighted ternary voting game ($\mathfrak{X}$); i.e., $\mathfrak{X}(S,T) : 3^N \longrightarrow \{-1,0,1\}$ [12].

$$\mathfrak{X}(S,T) = \begin{cases} 1, & \text{if } \mathscr{W}(S) \geq \mathfrak{P} \text{ and } \mathscr{W}(T) < \vartheta \\ -1, & \text{if } \mathscr{W}(S) < \mathfrak{P} \text{ and } \mathscr{W}(T) \geq \vartheta \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

$$\text{s.t.,} \quad \mathfrak{P} = \alpha \times \left(\sum_{i=1}^{n} \mathscr{F}_{m_i}(x) \right) \\ \text{and } \vartheta = \beta \times \left(\sum_{i=1}^{n} \mathscr{F}_{m_i}(x) \right) \tag{15}$$

2.3. Communication and Computation Resource Allocation Mechanisms. Wireless bandwidth is a valuable and scarce resource in the SFIoT system. Therefore, the limited wireless bandwidth has to be shared fair-efficiently by mobile users. If the allocation method is not considered explicitly at the design stage of bandwidth allocation algorithms, different bandwidth requests can result in very unfair bandwidth allocations; it may lead to a system inefficiency. Usually, various bandwidth allocation methods can be categorized into three ways: proportional allocation (PA), constrained allocation (CA), and equal loss allocation (EA) ways.

(I) Proportional allocation (PA)

$$A_i = R_i, \quad \text{if } \sum_{i=1}^{n} R_i \leq \mathfrak{B} \\ A_i = \max\left\{ \left(R_i \times \frac{\mathfrak{B}}{\sum_{i=1}^{n} R_i} \right), \mathscr{m}_i \right\}, \quad \text{otherwise} \tag{16}$$

(II) Constrained allocation (CA)

$$A_i = R_i, \quad \text{if } \sum_{i=1}^{n} R_i \leq \mathfrak{B} \\ A_i = \max\left(\min\left\{ R_i, T^C \right\}, \mathscr{m}_i \right), \quad \text{otherwise} \\ \text{s.t.,} \quad \sum_{i=1}^{n} \min\left\{ R_i, T^C \right\} = \mathfrak{B} \tag{17}$$

(III) Equal loss allocation (EA)

$$A_i = R_i, \quad \text{if } \sum_{i=1}^{n} R_i \leq \mathfrak{B} \\ A_i = \max\left\{ \left(R_i - \mathscr{L}^C \right), \mathscr{m}_i \right\}, \quad \text{otherwise} \\ \text{s.t.,} \quad \sum_{i=1}^{n} \max\left\{ \left(R_i - \mathscr{L}^C \right), 0 \right\} = \mathfrak{B} \tag{18}$$

where $\mathfrak{B}$ is the total available bandwidth amount and $\mathscr{m}_i$ is the predefined minimum bandwidth amount for the i^{th} service. $R_{1\leq i\leq N}$ is the bandwidth request of mobile device m_i, and $A_{1\leq i\leq N}$ represents the decided bandwidth amount for m_i. T^C and $\mathscr{L}^C$ are the constraint thresholds, which are chosen to satisfy each condition. If the available bandwidth is enough or the F-AP can secure the new request A_i from m_i through the allocated bandwidth readjustment, the new requested application is accepted. Otherwise, the new requested application is rejected.

In our bandwidth allocation algorithm, each F-AP decides its resource allocation way based on the weighted ternary voting game. In $\mathscr{F}_k^{AP}$, consider the $\mathfrak{X}$ game with $\mathbb{N}_{\mathscr{F}_k^{AP}}$. Individual $m_i \in \mathbb{N}_{\mathscr{F}_k^{AP}}$ participates in the voting procedure with his voting weight. Usually, the PA way is the most common method, and it can be seen as implicit consent. Therefore, for each voter, we can assume that there are three options, i.e., pro-CA, pro-EA, and abstention. According to (14), the coalition S consists of pro-CA voters, and the coalition T consists of pro-EA voters. If the outcome of $\mathfrak{X}(S,T)$ is 1 or -1, $\mathscr{F}_k^{AP}$ simply adopts the CA way or the EA way, respectively, in the bandwidth allocation process. If the outcome of $\mathfrak{X}(S,T)$ is 0, $\mathscr{F}_k^{AP}$ adopts the PA way. Based on the decisions of individual devices, Each F-AP adaptively decides its communication resource allocation way.

Like as the communication resource, computation capacity in each F-AP is also a naturally limited resource. Therefore, the computation power of F-AP is adaptively assigned to each requested application task. Usually, different applications can be categorized into two classes: class I (real-time data applications) and class II (non-real-time data applications) according to the required QoE. They not only require different computation capacity, but also have different QoE. In order to design the computation resource allocation algorithm, each F-AP needs to partition its own computation power to support different type applications. In this paper, we also adopt the weighted ternary voting game model. However, in contrast to the voting game in our communication allocation algorithm, the developed computation allocation algorithm has focused on the basic concept of pseudo-Banzhaf values.

Consider another $\mathfrak{X}$ game in $\mathscr{F}_k^{AP}$ with $\mathbb{N}_{\mathscr{F}_k^{AP}}$. Individual $m_i \in \mathbb{N}_{\mathscr{F}_k^{AP}}$ participates in the second voting procedure. At this time, there are three options for each voter, i.e., proclass I service, proclass II service, and abstention. According to (14), the coalition S consists of pro-class I service voters, and the coalition T consists of pro-class II service voters. Based on the outcome of $\mathfrak{X}(S,T)$, the F-AP estimates the preference ratio (α_I) of class I application services as follows;

$$\alpha_I = \frac{\sum_{m_i\in S} \left(\Psi_{m_i}^{\mathcal{Q}} \times \mathscr{F}_{m_i}(x) \right)}{\left(\sum_{m_i\in S} \left(\Psi_{m_i}^{\mathcal{Q}} \times \mathscr{F}_{m_i}(x) \right) + \sum_{m_j\in T} \left(\Psi_{m_j}^{\mathcal{Q}} \times \mathscr{F}_{m_i}(x) \right) \right)} \tag{19}$$

According to each user's pseudo-Banzhaf value and social power, the α_I value is decided, and each F-AP partitions its total computation capacity ($\mathscr{C}$). The division ratio for class I (*or* class II) type application services is α_I (*or* $1-\alpha_I$). And then, the partitioned computation capacity is distributed for its corresponding type application services while maximizing

Table 2: Application service type and requirements and system parameters.

Type	Application	Bandwidth requirement	Minimum requirement (m)	Computation requirement	Duration (Ave./sec)
Class I	Application I	A=512 Mbps	A=256 Mbps	98 MHz	180 sec
	Application II	A=640 Mbps	A=320 Mbps	256 MHz	120 sec
Class II	Application III	A=768 Mbps	A=384 Mbps	128 MHz	240 sec
	Application IV	A=896 Mbps	A=458 Mbps	256 MHz	300 sec
	Application V	A=1.28 Gbps	A=640 Mbps	384 MHz	360 sec
	Application VI	A=1.52 Gbps	A=860 Mbps	512 MHz	480 sec

Parameter	Value	Description
Γ	5	the maximum outcome of a user to normalize the social power
μ	0.9	a parameter to controls the speed of social power saturation
α	0.75	a factor to decide the quota for the decision-taking
β	0.25	a factor to decide the quota for the decision- blocking
η_I	0.9	a control parameter to adjust the payoff of class I service
η_{II}	0.7	a control parameter to adjust the payoff of class II service
ε	10	a control parameter for the sharing activity between social friends

the system performance. To implement this process, we adopt the fundamental notion of the Nash Bargaining Solution (NBS). This is captured by the following optimization problem.

$$\max_{[\ldots A_{m_i}\ldots]} \prod_{m_i \in S} U^{I}_{m_i}\left(A_{m_i}\right) + \max_{[\ldots A_{m_j}\ldots]} \prod_{m_j \in T} U^{II}_{m_j}\left(A_{m_j}\right) \tag{20}$$

$$\begin{aligned} \text{s.t.,}\quad & U^{I}_{m_i}\left(A_{m_i}\right) = \eta_I \times \log_2\left(1 + \frac{A_{m_i}}{R_{m_i}}\right) \\ & U^{II}_{m_j}\left(A_{m_j}\right) = \eta_{II} \times \left(1 - \exp\left(-\frac{A_{m_i}}{R_{m_i}}\right)\right) \\ & \sum_{m_i \in S} A_{m_i} \le \left(\alpha_I \times \mathscr{C}_{\mathscr{F}^{AP}_k}\right) \\ & \text{and} \sum_{m_j \in T} A_{m_j} \le \left(\left(1 - \alpha_I\right) \times \mathscr{C}_{\mathscr{F}^{AP}_k}\right) \end{aligned} \tag{21}$$

where η_I ($or\ \eta_{II}$) is a control parameter to adjust the payoff of m_i ($or\ m_j$) and $\mathscr{C}_{\mathscr{F}^{AP}_k}$ is the total computation capacity of $\mathscr{F}^{AP}_k$.

2.4. Main Steps of Proposed SFIoT Resource Allocation Scheme. Under the vision of the future internet, the SIoT paradigm aims to connect anything while relying on the self-establishment of inter-thing social relationships. In addition, the emerging paradigm of FC exhibits the right features for coping with the aforementioned technological 5G network issues. In order to address this challenge, the SFIoT paradigm has been gaining momentum. To effectively operate the SFIoT system, the interactive relationship between F-APs and mobile devices is an important research topic and should be considered to design the resource allocation algorithms. In this study, we provide the communication and computation resource allocation scheme, which is formulated according to the BVG and NBS. Owing to our two-phase game model, we can get the most fair-efficient system performance by combining both game approaches. The main steps of the proposed scheme are described as follows.

Step 1. Application types, requirements, and system control parameters are determined by the simulation scenario (see simulation assumptions in Section 3 and Table 2).

Step 2. Each individual F-AP monitors its covering area and responds to its corresponding mobile devices. Mobile devices generate their application service requests in a distributed fashion and ask FC services to their corresponding F-AP.

Step 3. Each mobile device has its own social relationship through a social network; close friends can probabilistically share the outcome of FC services.

Step 4. To reduce computation complexity, individual F-APs execute separately their two-phase games in parallel.

Step 5. During the first game process, each mobile device takes two votes; one is to decide the communication resource allocation way and the other is to partition the F-AP's computation capacity.

Step 6. According to (14), the F-AP decides its communication allocation way. Based on our weighted ternary BVG model, one of the PA, CA, and EA ways is adaptively selected. And then, the F-AP estimates the division ratio of computation capacity using (19).

Step 7. During the second game process, each F-AP independently distributes the partitioned computation capacity to corresponding type applications. According to (20), different applications can retain their FC services while maximizing the system performance.

Step 8. Based on the two-phase game model, F-APs and mobile devices are hierarchically interconnected and interacting with one another to operate the SFIoT system.

Step 9. Constantly, each F-AP is self-monitoring its covering area. When the game players are changed due to the mobile device migration, the proposed scheme proceeds to Step 5 for the next two-phase game procedure.

3. Simulation Results and Discussion

In this section, we evaluate the effectiveness of our proposed protocol and analyze the simulation result while comparing it with that of the *SDFC* [14], *SSEC* [15], and *CFIC* [16] schemes. To ensure a fair comparison, the experimental setup consists of the following specifications and scenario.

(i) Simulated SFIoT system consists of 25 F-APs and 100 mobile devices; F-APs are laid out in regular pattern, and mobile is randomly located in the F-APs' covering areas.

(ii) For the FC services, total computation capacity of each F-AP is 30 GHz, and total communication resource of each F-AP is 50 Gbps.

(iii) Each mobile device individually generates service requests. Service type of applications is randomly decided, and service request rate is Poisson process (ρ). The offered rate range is varied from 0 to 3.0.

(iv) The social friend number ($|\mathbb{S}_m| > 0$) of each mobile device is a random variable, which has the maximum probability at 3 while following a normal distribution.

(v) Each social tie ($0 \leq e_{m,m} \leq 1$) between mobile devices is also a random variable, which has the maximum probability at 0.5 while following a normal distribution.

(vi) The probability ($\mathcal{P}_s$) that social friends m_i and m_j can share the service outcome is defined as $\mathcal{P}_s = e_{m_i,m_j}/\varepsilon$, where ε is a control parameter for the sharing activity.

(vii) We assume that there are no physical obstacles in the experiments and each mobile device can contact its corresponding F-AP for FC services.

(viii) For calculation simplicity, the communication resource is specified in terms of basic units (BUs), where one BU is the minimum amount (e.g., 128 Mbps in our system) of resource management.

(ix) Using the iterative water-filling method, the value of NBS in (20) is obtained.

(x) Network performance measures obtained on the basis of 100 simulation runs are plotted as functions of the offered service request rate (ρ).

(xi) Six different applications are assumed based on the different computation and communication requirement; they are generated with equal probability.

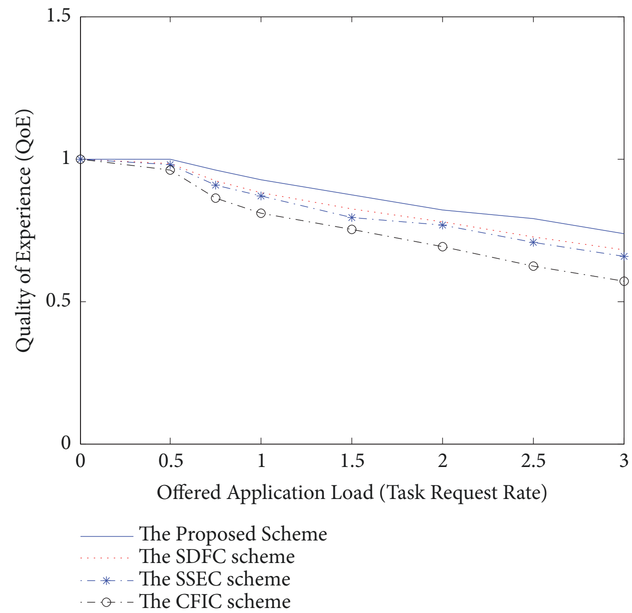

Figure 1: SFIoT quality of experience (QoE).

(xii) Performance criteria obtained through simulation are QoE, resource usability and task failure probability; these simulation metrics are evaluated mainly to demonstrate the validity of our proposed method.

To facilitate the development and implementation of our simulator, Table 2 lists application service type, requirements, and system control parameters.

Figure 1 shows the QoE of each scheme in different application load scenarios. For this evaluation, QoE is defined as the normalized resource loss ratio than the originally requested amount. From the viewpoint of mobile users, QoE is a key factor to evaluate their service satisfactions. In the proposed scheme, the system resource is differently allocated based on the voting approach. According to the desirable features of ternary voting approach, the limited resource can be assigned while effectively reflecting the preference inclination of users. Our two-phase game approach can well orchestrate the SFIoT system infrastructure to maximize the QoE of mobile users. The result of Figure 1 proves that our two-step game method is a socially beneficial way to achieve a better QoE than other existing schemes.

The obtained results of task failure probabilities are depicted in Figure 2. This performance criterion is strongly related to the SFIoT system throughput, which is estimated based on the ratio of successfully completed applications. As expected, the application load increases, the available system resource is exhausted to support new application services. Therefore, task failure probabilities increase proportionately with the application request rate. The resulting curves in Figure 2 allow us to see that our proposed scheme has gained a lower task failure probability than other existing schemes. It is therefore worth to say that, under different application load conditions, our proposed scheme can perform excellently to maintain a superior system throughput based on the

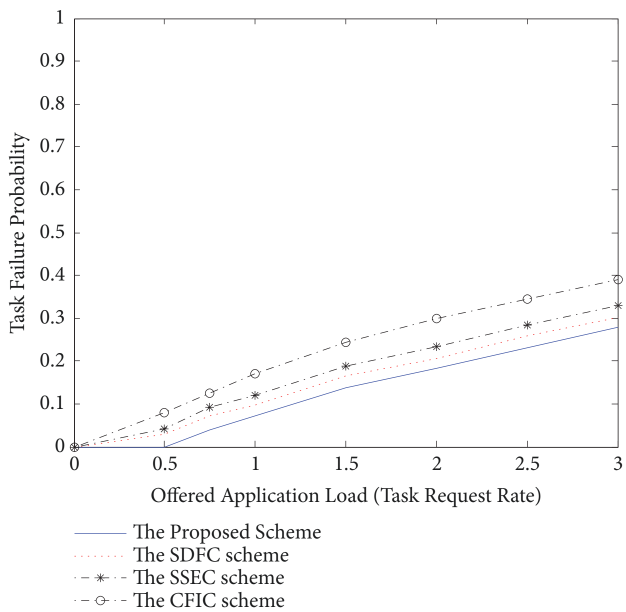

Figure 2: SFIoT task failure probability.

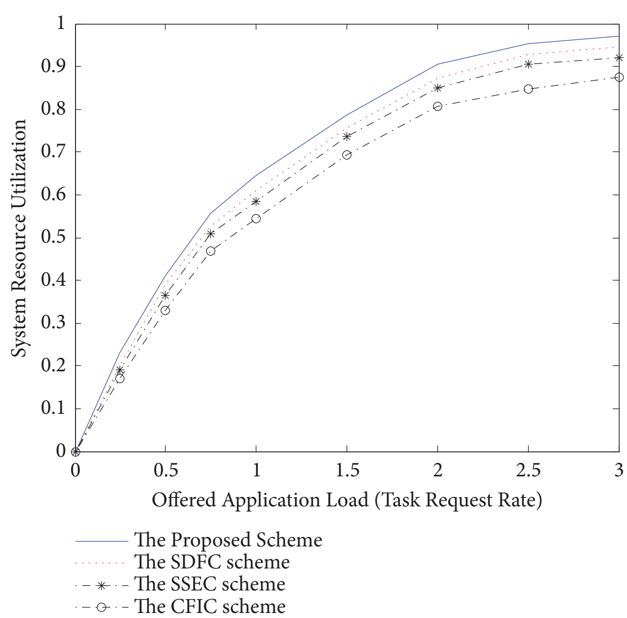

Figure 3: Resource utilization.

self-controlled management policies. It is a highly desirable property for the SFIoT system operations.

Figure 3 illustrates the resource utilization of F-APs. We measure this performance metric to show and determine whether our game-based approach can provide the system efficiency. As it was explained, control decisions in the proposed scheme are made in an interactive two-phase game model. More specifically, the proposed approach in this paper can adapt the current SFIoT system condition while dynamically adjusting the control decisions. When the application load is low (below 0.5), the performance of each scheme is not much difference. As the application load rate increases, the resource utilization also increases. All the schemes have similar trends; however, due to our approach's flexibility, adaptability, and responsiveness to current SFIoT system conditions, the F-AP resource in our proposed scheme can be used more efficiently under widely different and diversified application load situations.

Through simulation experiments, the obtained results in Figures 1–3 clearly demonstrate that the suitability and feasibility of our proposed scheme while revealing enhanced perspectives regarding QoE, throughput, and resource utilization in the SFIoT system. In particular, the BVG and NBS processes work together to reach an agreement that gives mutual advantages for mobile devices and F-APs; two game models are sophisticatedly combined and dependent on each other. Therefore, they act cooperatively to satisfy the different performance requirements.

4. Summary and Conclusions

The past decade has witnessed an explosive growth of IoT, where a variety of smart mobile devices offer a plethora of different applications. Under the vision of future networks, FC and social network principles are integrated into the IoT paradigm in order to enforce the distributed self-cooperation and self-management of mobile devices. In this paper, we present a novel resource allocation scheme for the SFIoT system. According to the BVG and NBS approaches, our proposed scheme is designed as two phases: (i) mobile devices take votes to decide the resource allocation methods based on the weighted ternary BVG model and (ii) the partitioned computation capacity is fair-efficiently distributed to each application by using the NBS. These two game models continue iteratively in a step-by-step manner in accordance with the current SFIoT system information. The experimental simulation results prove that our proposed protocol can efficiently improve the QoE, system throughput, and resource utilization, compared with the existing *SDFC*, *SSEC*, and *CFIC* schemes. As directions for future research, we aim at investigating the privacy and energy issues for the SFIoT system. We especially plan to add a blockchain-based security layer to the system. In addition, we also plan to develop a noncooperative game model with theoretical analysis and will focus on the addition of more features to increase the SFIoT system reliability in an unconstrained environment. Last, but not least, machine learning techniques can be applied to complement our proposed scheme. It will be a potential direction and another possible extension to this work.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

Authors' Contributions

The sole author contributes to all research work.

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