Joint Distributed Cache and Power Control in Haptic Communications: A Potential Game Approach

Tao Fang, Dan Wu, Jiaxin Chen, *Graduate Student Member, IEEE*, Chao Yue, and Meng Wang

***Abstract*—Since haptic communications have an extreme requirement for the latency performance, the overdue content delivery will decrease the application experience. In order to reduce the transmission delay, we try to construct a cache-enabled D2D-assisted content-sharing framework, where the neighboring helpers preset contents and adjust their transmission power to timely serve more requesters. In particular, we modify the existing definition of the "closest" friend and take the social relationship into account to measure the overall influence caused by available neighboring helpers. However, such cooperation consumes the storage space and energy of the helpers, and accordingly, we introduce blockchain technology to propose an effective incentive mechanism where the helpers act as consensus users of blockchain and obtain the reward, i.e., the allocated computing power by the base station (BS), by contributing their local resources. Guided by this, the benefit of each helper is defined as a tradeoff of the reward and overheads. Meanwhile, we formulate the multiuser content delivery problem with the goal of maximizing the global benefits as the multiuser content delivery game. Then, we prove that the proposed game is an exact potential game (EPG) with at least one pure-strategy Nash equilibrium (NE). Meanwhile, the context-aware content delivery-based concurrent better reply (CCDCBR) algorithm is proposed to achieve a desirable solution. Finally, simulation results verify the validity of the proposed game model as well as the proposed algorithm.**

***Index Terms*—Blockchain, distributed cache, haptic communications, potential game, power control.**

I. INTRODUCTION

A. Research Background and Motivation

IN THE smart city based on Internet of Things (IoT), besides the audio and video, mobile users desire fresh sensory stimulation in another dimension, i.e., tactile perception [1]. A tactile perception is a direct form of expression of haptic feedback which consists of tactile perception and kinesthetic perception [2]. Through haptic feedback, mobile users can intuitively feel force caused by the external environment and understand the texture of unknown objects [3]. Take remote surgery as an example, the doctor can sense and analyze the state of an illness of the remote patient by the haptic device. Thus, these advantages have given birth to haptic communications.

However, haptic communications are still in the beginning stage. The key problem in haptic communications is 1-ms challenge [4]. That is, experiencers must accept the haptic feedback within 1 ms, which is decided by the perception of human. Due to the fact that transmission delay is dominant in a round-trip latency, the quick content response by content delivery can decrease the transmission delay. Hence, studying the timely and reliable content delivery is of importance for haptic communications.

The traditional centralized data storage structure is no longer applicable. That is due to the following facts.

1) A huge massive IoT devices or sensors are deployed to collect related audio, video, and even haptic information, and they update the related information periodically by delivering such information from the sensor layer to the storage layer constantly. As such, the amount of data in the storage layer will be enormous as time goes by.
2) The storage structure influences the content response speed. Once the storage location of desired documents is far away from the requester, the service delay will be longer.

A promising solution to address the above challenge is the distributed cache [5]–[7]. Through this technology, related data is cached in nearby users, i.e., neighbors. When some users want to obtain heat documents, they can get files from their neighbors via Device-to-Device (D2D) communications [8]–[10], which enable to decrease the service delay and improve the service quality.

Although distributed cache can improve the response speed, the successful content delivery mainly depends on the local content cache and suitable transmission power. An effective content preset can be realized by the distributed cache so that the desirable contents are in the proximity of requesters. The transmission power not only influences the content delivery performance of D2D links but also decides the selection of requesters' "closest" friend, a neighbor with strong transmission performance. Thus, it can be seen that both the distributed

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cache and power control can improve the content delivery. Unfortunately, most works only focus on the distributed cache or power control, the joint optimization is ignored. When studying the joint optimization, the great challenge is exploring the mutual relationship between the distributed cache and power control.

More significantly, most of the existing works, e.g., [11]–[13], assume that neighbors/helpers are altruistic and helpful to share their documents without remuneration. Nevertheless, this assumption is against the fact, that is, since these helpers in reality are selfish and rational, and they have limited energy [14], [15], no neighbor wants to share its local contents with the requesters at the cost of energy consumption. Therefore, it is necessary to design an effective incentive mechanism where the helpers are willing to help others realize the content delivery by caching and adjusting their power.

To make the proposed incentive mechanism suitable for the distributed storage of haptic communications, we introduce blockchain to design the incentive mechanism. Blockchain is regarded as a distributed public ledger without a centralized trust mechanism [18]–[20]. Instead, the trust mechanism of blockchain is maintained by multiple consensus users who conduct the consensus mechanism, i.e., Proof of Work (PoW) protocol [21], to achieve the consensus state. Once data are written into the blockchain, this behavior will be recorded and the written data, e.g., transaction time and transaction fee, cannot be tampered forever, which protects the security of transaction information. However, the operation of PoW involves the solution of a math puzzle, which needs a certain computing power. The computing power of consensus users, i.e., relative power, is allocated by the base station (BS) according to a certain principle. Therefore, there exists a great difficulty in designing the incentive mechanism, which is presented as follows.

1) *How to Associate Blockchain With the Distributed Cache:* When the neighbors act as consensus users of blockchain, they have computing demand while others have content demand. The real goal is to realize the cooperation of neighbors for local content sharing. The focus of the incentive mechanism is that consensus users can get a certain computing resource by contributing their local resources.
2) *How to Guarantee Fairness in the Incentive Mechanism:* The fairness among users should be strictly guaranteed, which involves the construction of a reward function. In a reasonable incentive mechanism, the rewards of users are proportional to their efforts. This design is helpful to the fair competition of users who aim to obtain a higher reward by adjusting their decisions.

B. Related Work

In this section, we review the related existing works and summarize them as the following categories.

1) Haptic Communications and Distributed Cache: The research of haptic communications is still in the beginning [22]. The definition of Tactile Internet and haptic communications is given in [23] where Tactile Internet is "a network of networks." In [24], the wearable sensor as a haptic device is used to collect the skin information of patients to predict the hydration level by machine learning. She *et al.* [25] studied the cross-layer transmission design and proposed a proactive packet dropping mechanism, which aims to guarantee the QoS requirements. Meanwhile, Wei *et al.* [26] innovatively combined the haptic communications with smart city and developed a Tactile Internet framework for a smart city. The work in [27] and [28] introduced human-in-the-loop mobile networks and studied the radio resource allocation in haptic communications. Specifically, to analyze the mutual relationships of cross-modal signals, Zhou *et al.* [29] proposed the cross-modal collaborative communications and developed a cross-modal data reconstruction architecture.

Aijaz *et al.* [30] investigated the significance of timely demand response in haptic communications. When requesters cannot get the service, the experiencers of haptic applications will feel the obvious "cyber-sickness," i.e., the bad game experience. Najeh and Bouallegue [31] proposed a mode selection approach involving the cellular and D2D users, and investigated the distributed power control from a game-theoretical approach. However, this work ignores the influence of local resources on power control which is not suitable in this article. Sukhmani *et al.* [32] pointed out that the distributed cache can improve the service performance of haptic applications, i.e., AR/VR. Some information, e.g., the background information, may be requested repeatedly by the haptic applications. Thus, users share their local content resources between neighbors to timely respond to the demand of requesters. Finally, it will greatly shorten the service delay of haptic applications. Nevertheless, the cooperation willingness is not discussed in [32].

Meanwhile, the performance of service response is related to the match of content responders and requesters. Yang *et al.* [34], ElSawy *et al.* [35], and Jo *et al.* [36] explored the establishment of the service relationships. In their proposed system model, a closest friend of requesters with content demands is defined to provide the timely content delivery service. However, the above studies only characterize the friend relationships from the perspective of the physical factor. The social relationship between the requester and content responder is ignored but important. Thus, the definition of the closest friend should be redesigned.

2) Blockchain in the Incentive Mechanism: Although there exist great advantages when introducing the distributed cache, most of the existing works ignore the fact that users are rational and selfish in practice. Thus, from a practical point of view, we should take the selfishness of users into account and redesign the cooperation mechanism.

Currently, a few works have been conducted where the blockchain technology is introduced to motivate adjacent users to share their local resources. Wang *et al.* [37] used the smart contracts of blockchain to develop a content caching market where the cache helpers are motivated to keep active in service. Seng *et al.* [38] established a blockchain-based platform where requesters with content demands are matched with responders

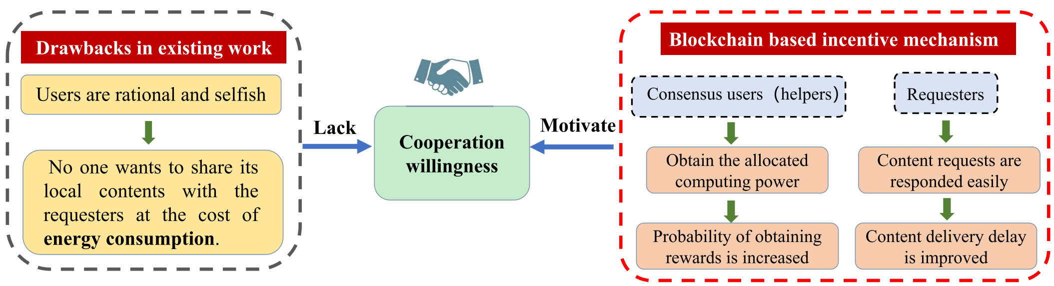

Fig. 1. Illustration of the proposed blockchain-based incentive mechanism.

by the proposed matching algorithm. Liu *et al.* [39] proposed a wireless blockchain framework where the computation task of miners can be offloaded to nearby nodes and the block data can be cached into the edge server. An innovative proactive caching scheme was proposed based on the hierarchical blockchain framework in [40], where the total system consists of two layers and each layer keeps one unique ledger. Cui *et al.* [41] investigated the relationships between the allocated computing power and the size of shared contents, finally proposed a blockchain-based caching placement scheme.

Thus, these existing works reflect the fact: the blockchain technology is a promising way to solve the problem of the incentive mechanism in content delivery networks. However, when the blockchain is applied in haptic communications, the new challenge emerges. For example, from the perspective of consensus users, how to design the reasonable utility function to associate the decisions with the benefits or rewards of blockchain. To the best of our knowledge, the combination of haptic communications and blockchain has not been well investigated in the existing works.

C. Main Contributions

In this article, we investigated the content delivery problem in haptic communications to achieve a quick content response. The contributions of this article can be summarized as follows.

1) We propose a cache-enabled D2D-assisted content-sharing framework where transmission delay can be decreased by timely content delivery in haptic communications. To overcome the selfishness of neighbors, we design an effective blockchain-based incentive mechanism as shown in Fig. 1. The focus is that helpers act as consensus users and share their local resources to receive the reward, i.e., the computing power allocated by the system. Meanwhile, the definition of the closest friend is modified by integrating with the social relationship to measure the overall influence caused by available neighboring helpers.
2) In the above context, we model the distributed cache and power control as a multiuser content delivery game, whose goal is to maximize the individual benefits, i.e., a tradeoff of the received expected revenue and overheads caused by energy and storage consumption, by making the 2-D decisions. Different from the traditional local altruistic game, we extend it to the potential cooperation game. In the proposed game, the potential cooperation neighbors are considered to analyze the resource competition between multiple users. Meanwhile, we prove the existence of Nash equilibrium (NE) points in our proposed game, which is an exact potential game (EPG). The corresponding NE points are the solution to the optimization problem.
3) We propose the context-aware content delivery-based concurrent better reply (CCDCBR) algorithm to find the desired solution. To make the proposed algorithm suitable for the 2-D decisions, we modify the better reply algorithm and introduce the concept of concurrent execution into it to improve the performance of the proposed algorithm, i.e., increase the convergence rate.

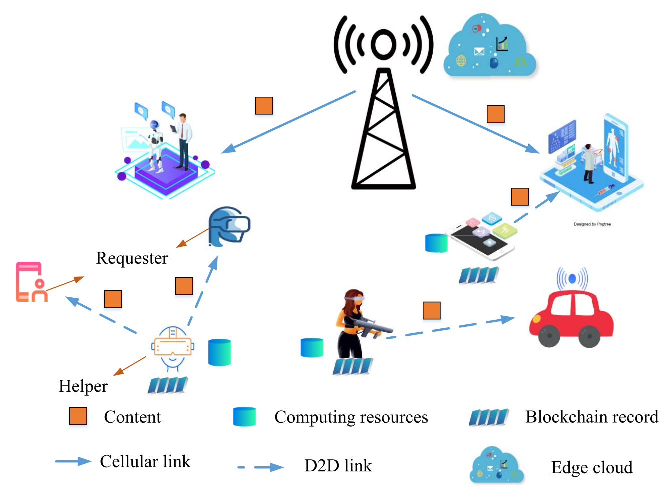

Fig. 2. Edge cache scenario in haptic communications.

The remainder of this article is organized as follows. We present the system model and problem formulation in Section II. Next, we formulate the multiuser content delivery game in Section III. Then, the proposed algorithm is given in Section IV. Finally, the related simulation results and conclusion are presented in Sections V and VI, respectively.

II. System Model and Problem Formulation

A. System Model

We consider an edge cache scenario in haptic communications. As shown in Fig. 2, there exists a BS equipped with an edge cloud to provide communication service. Meanwhile,

TABLE I
KEY VARIABLES USED IN THIS ARTICLE

Variables	Explanation
M	Number of requesters
N	Number of helpers
F	Number of documents in library
$\mathcal{F}$	System content library
$P_{m,f}$	Probability of requesting document f for requester m
a_n	Action of helper n
c_n	Cache contents of helper n
p_n	Transmission power of helper n
MC	Size of cache space
α_n	Relative power of helper n
d_{th}	Commnication threshold
E_n	Expect reward of helper n
R	Fixed reward
r	Variable reward factor
t_n	Number of transactions of helper n
β_n	Verification probability of helper n
$P_{orphaning}$	Probability of orphaning
λ	Related Poisson parameter
D_f	Corresponding data size of content f
C_1	Overhead per power
C_2	Overhead per bit

there are M mobile users, i.e., $\mathcal{M} = \{1, 2, \ldots, M\}$, are running haptic applications, e.g., the remote surgery. These application experiencers (called requesters for brevity) request some special contents according to their unique application demands, i.e., the background information of AR/VR. We assume that all desirable documents are from system content library $\mathcal{F} = \{1, 2, \ldots, F\}$, where F denotes the number of documents in library. Specifically, requesters request their interested files according to a certain popularity distribution, i.e., Zipf distribution. The probability of requesting document f for requester m is presented as follows:

$$P_{m,f} = \frac{1/f^{\gamma_m}}{\sum_{i=1}^{F} 1/i^{\gamma_m}} \tag{1}$$

where γ_m denotes the popularity parameter, and the value of γ_m reflects the degree of skewness.

In addition, there are N helpers which act as consensus users, i.e., $\mathcal{N} = \{1, 2, \ldots, N\}$. These helpers running the blockchain application, e.g., DApp [33], are responsible for maintaining the consensus mechanism. Specifically, they mine the new block to store transaction information. Moreover, the process of mining in essence is obtaining the solution of the math puzzle. The consensus user who solves the math puzzle first will receive the reward given by the system. However, the mining speed is related to the computing power. In other words, a consensus user wants to mine a block quickly in a shorter time, then it needs more computing resources. The key variables are given in Table I.

On the one hand, when requesters merely rely on the response and service of BS, both the performance and experience may be affected due to nonnegligible delay. On the other hand, taking the available local content of helpers into account, helpers can share their corresponding cache when requesters generate content demands. Meanwhile, BS will allocate part of its computing resource as a reward to helpers who realize the content delivery. In this framework of cooperation, the content delivery delay of requesters is improved, and the probability of obtaining rewards of helpers is also increased.

B. Problem Formulation

We denote $a_n = (c_n, p_n)$ as the action of helper n, where $c_n = (c_{n,1}, c_{n,2}, \ldots, c_{n,\mathrm{MC}})$ and p_n denote the cache content and transmission power of helper n, and $\mathrm{MC} = |c_n|$ is the size of cache space. When helper n responds to the content demand of neighbors and shares its local cache via D2D communications, BS will allocate a certain computing power to help helper n solve the math puzzle according to the joint decision profile of all helpers. Given the action a_n of helper n, the allocated power, i.e., the relative power/hash power, is given by

$$\alpha_n = \frac{|s_n|}{M} \tag{2}$$

where M is the number of total requesters in networks, and s_n denotes the set of requests who select to access the service of helper n.

According to the existing works, requesters prefer to turn to their closest friend for service [34]–[36]. To measure the influence of the physical and social relationships on content delivery, we define the closest helper x_m of requester m as follows:

$$x_m = \arg\max \left\{ p_i h d_{i,m}^{-\alpha} \sum_{f \in \mathcal{F}} P_{m,f} H(f, c_i) \right\}, \quad i \in \mathcal{N}, m \in \mathcal{M} \tag{3}$$

where p_i is the transmission power of helper i, h is the normalized propagation parameter, $d_{i,m}$ denotes the physical distance between helper i and requester m, α is the path-loss exponent, and $P_{m,f}$ denotes the probability requesting content f. The function $H(f, c_i)$ indicates whether consensus user i caches content f, which is expressed as follows:

$$H(f, c_n) = \begin{cases} 1, & \text{if } f \in c_n \\ 0, & \text{if } f \notin c_n. \end{cases} \tag{4}$$

Equation (3) indicates that the decision of requester m is decided jointly by the physical factor, i.e., $p_i h d_{i,m}^{-\alpha}$, and social relationships, i.e., $\sum_{f \in \mathcal{F}} P_{m,f} H(f, c_i)$. As shown in Fig. 3, requester 1 will select the suitable helper to get content service according to the physical factor and social relationship. Specifically, the black solid line and red dotted line denote the physical factor and the social relationship between the helper and requester, respectively. The ellipse indicates the communication range because of the transmission power. In Fig. 3(a), requester 1 is only within the communication range of helper 2, then requester 1 selects helper 2 to acquire the

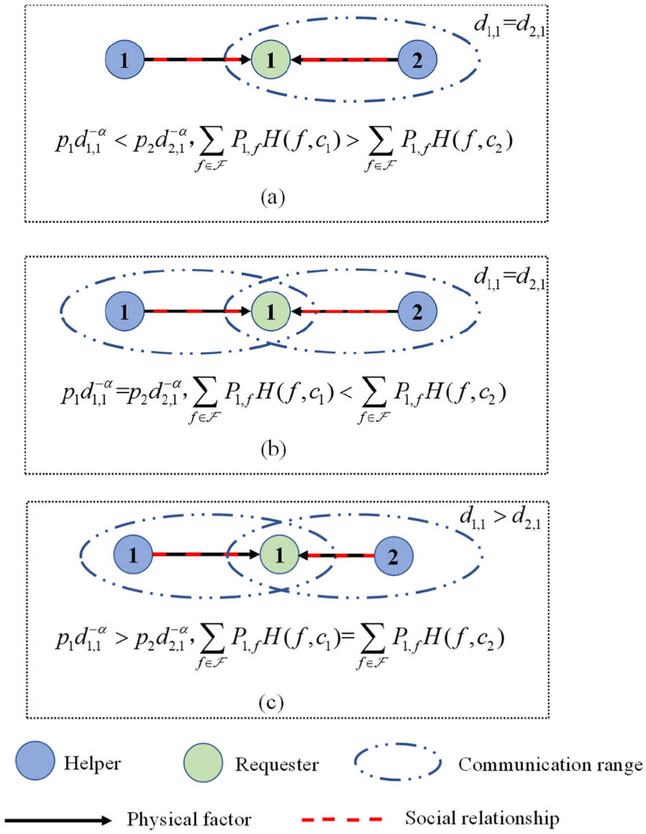

Fig. 3. Illustration of service relationships between consensus users and requesters, where (a) shows the distances from requester 1 to two helpers are the same, (b) shows the physical factors for two helpers are the same, and (c) shows the social relationships for two helpers are the same.

content service. In Fig. 3(b), there exist two neighbor helpers, i.e., helpers 1 and 2, around requester 1. Requester 1 receives the same level of physical factors from helpers 1 and 2 due to equal distance and transmission power. However, helper 2 with a strong social relationship will give requester 1 quick service response. Then, requester 1 will establish a service relationship with helper 2. However, in Fig. 3(c), when facing the same social relationship from neighbors, requester 1 will select helper 1 to obtain service. The reason is that although requester 1 has a closer distance, helper 1 can bring requester 1 a higher transmission experience due to a great physical factor.

Thus, the set of requesters paired with helper n, i.e., S_n, is defined in (5), shown at the bottom of the page. In (5), $d_{\rm th}$ is the communication threshold, which is related to the transmission power of helpers. When a helper adjusts its power to a high one, then the corresponding threshold will increase.

Given the action of helper n, i.e., the cache and transmission power, then the expect reward of helper n is defined as follows:

$$E_n = (R + rt_n) \cdot \alpha_n \cdot \beta_n \tag{6}$$

where r is a variable reward factor, R and rt_n denote a fixed reward and variable reward, respectively. t_n is the number of transactions, which is stored in a new block mined by helper n. α_n is the relative power that decides the speed of mining a block. Note that α_n only influences the probability of mining a new block. In fact, when helper n mines out a new block, it still needs to transmit its mined block to other helpers to verify the correctness. Once the new block is verified, then helper n receives the reward. Accordingly, β_n indicates the probability that the new block mined by helper n is verified successfully by others, which is given by

$$\beta_n = 1 - P_{\rm orphaning} \tag{7}$$

where $P_{\rm orphaning}$ denotes the probability of orphaning where the new block will be discarded due to the long block propagation delay [42]. The block propagation delay is proportional to the block size. Meanwhile, according to the existing works [43], [44], time for mining a block and the corresponding block size follow the Poisson distribution and normal distribution, respectively. Thus, the probability of orphaning $P_{\rm orphaning}$ is expressed as follows:

$$P_{\rm orphaning} = 1 - e^{-\lambda z t_n} \tag{8}$$

where λ is the related Poisson parameter, and z is the delay factor, which is a fixed constant. And t_n denotes the number of transactions of helper n, i.e., the block size of helper n.

In addition, taking the overhead of helper n caused by energy and storage consumption, the benefit of helper n is presented as follows:

$$u_n = (R + rt_n) \cdot \frac{|S_n|}{M} \cdot e^{-\lambda z t_n} - C_1 p_n - C_2 \sum_{f\in c_n} D_f \tag{9}$$

where p_n is the transmission power of helper n, and D_f is the corresponding data size of content f, thus, $\sum_{f\in c_n} D_f$ indicates the aggregate storage space due to cache contents. C_1 and C_2 indicate the overhead per power and per bit.

The first term of (9) denotes the expect reward, and the second and last terms indicate the energy consumption and storage consumption, respectively. Moreover, in order to obtain the great benefits, helpers will adjust their actions, i.e., adjust their transmission power and cache. As can be seen from Fig. 4 and (5), there exist three typical scenarios in this considered model.

1) *Scenario 1:* In Fig. 4(a), there exists one requester within the overlapping communication ranges of helpers 1 and 2. Given the current action of helpers, requester 1 chooses helper 2 to establish service relationships. Meanwhile, helper 1 can adjust its power/cache contents to attract request 1 to obtain the high benefit.
2) *Scenario 2:* In Fig. 4(b), some requesters merely located in the communication range of helper 1, and these

$$S_n = \left\{ m : d_{n,m} \le d_{th}, p_n h_n d_{n,m}^{-\alpha} \sum_{f\in\mathcal{F}} P_{m,f} H(f, c_n) = \max\left\{ p_i h_i d_{i,m}^{-\alpha} \sum_{f\in\mathcal{F}} P_{m,f} H(f, c_i) \right\}, i \in \mathcal{N} \right\} \tag{5}$$

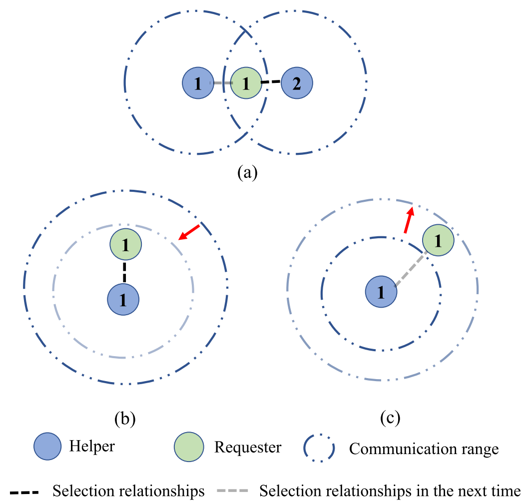

Fig. 4. Illustration of three typical scenarios in this considered model, where (a) shows the requester is within the overlapping communication range of helpers, (b) shows helper 1 will decrease the transmission power to save energy consumption, and (c) shows helper 1 will increase the transmission power to attract helper 1.

requesters establish the service relationships with helper 1. Helper 1 can decrease its transmission power to save its energy consumption.

3) *Scenario 3:* Given the action of helper 1 as shown in Fig. 4(c), there are some requesters without but near the communication range of helper 1. Meanwhile, helper 1 can increase its power to attract the potential requesters to improve its benefit.

Thus, the system benefits involving all helpers are presented as follows:

$$U = \sum_{n \in \mathcal{N}} u_n. \tag{10}$$

Helpers can obtain the high reward by responding to the content demand of requesters, BS allocates computing resources to helpers who realize the content delivery. Finally, a potential cooperation mechanism is formed. From the perspective of the global system, the goal is to maximize the aggregate benefits of all helpers, which is expressed as follows:

$$P1 : a_{\text{opt}} \in \underset{a=(a_1,a_2,\ldots,a_N)}{\arg\max} \quad U \tag{11}$$

where $a = (a_1, a_2, \ldots, a_N)$ is the action profile of all consensus users.

From (11), we can conclude that the optimization problem $P1$ is a complicated and combinational problem, which involves the decisions of all helpers. The traditional centralized approach, e.g., a center controller, can solve the corresponding problem. However, it will face the high complexity and great calculation. Especially, when the number of helpers rises, the complexity will increase explosively. Therefore, to deal with the challenge, we introduce the game theory and solve it innovatively in a distributed manner.

III. Multiuser Content Delivery Game

A. Game Model

Game theory as a branch of modern mathematics has been widely used in wireless communication. Generally, researchers use game theory to characterize and analyze the competition between multiple game players. Each player can adjust its action according to the current communication environment, e.g., the response of other players to the competition of communication resources. Through constant iteration and update, finally, all game players will achieve a stable point where no one wants to change their decision unilaterally.

Inspired by [45] and [46], jointly optimizing the distributed cache and power control is the Pareto-optimal problem. In this section, we combine game theory with the optimization problem and obtain a desirable solution from a distributed framework. Specifically, we formulate the problem $P1$ as a multiuser content delivery game, i.e., $\mathcal{G} = \{\mathcal{N}, A_n, U_n\}$, where $\mathcal{N}$ denotes the set of game players, i.e., the consensus users. A_n indicates the strategy space of consensus user n, i.e., $A_n = \{a_n : a_n = c_n \otimes p_n, c_n \subset \mathcal{F}, p_n \in \mathcal{P}\}$, where c_n and p_n are the cache content of consensus user n and the transmission power of consensus user n, respectively. Moreover, $\mathcal{F}$ is the system document library, and $\mathcal{P}$ is the set of the available transmission powers. Finally, U_n is the utility function of player n, which is the key point of our proposed game. The design of the utility function determines whether there exists one stable solution, i.e., NE points.

In our game model, the concept of local altruistic cooperation in [47] is applied. The local altruistic cooperation means that when every player takes its action and updates its decision, they should also consider the utility of neighbors besides its utility. Meanwhile, in the existing works of local altruistic cooperation, the neighbors of every game player are predetermined due to the equal transmission power of all game players. However, the traditional local altruistic cooperation is not suitable for our optimization problem. The reason is that the transmission power of all game players is not fixed in our game model, and every player can adjust its transmission power to pursue the high benefits.

Thus, we extend the traditional local altruistic game to a local potential game where our proposed game considers the potential cooperation between multiple players. To characterize the potential cooperation of players, we define the set of potential cooperation neighbors of player n, which can be expressed as follows:

$$\mathcal{J}_n = \left\{ j \in \mathcal{N} : d_{n,j} < d_{th}^{p_{n,\max}}, n \in \mathcal{N} \right\} \tag{12}$$

where $d_{n,j}$ is the physical distance between consensus user n and j, and $p_{n,\max}$ and $d_{th}^{p_{n,\max}}$ are the maximum transmission power of player n and the corresponding communication threshold of player n, respectively.

We introduce the potential cooperation into the utility of player n, which can be presented as follows:

$$U_n(a_n, a_{-n}) = u_n(a_n, a_{-n}) + \sum_{i \in \mathcal{J}_n} u_i(a_i, a_{-i}). \tag{13}$$

Note that (13) consists of two parts: 1) its utility and 2) the utilities of potential cooperation neighbors. This design of utility function inherits the mind of local cooperation. It can be explained that when any player changes its action, the new action will influence the global benefits of the system. However, the updating player only influences its potential cooperation neighbors due to the constraint transmission power. Thus, in other words, when one game player updates its action, the utility of both this updating player and its potential cooperation neighbors will be affected, i.e., increase or decrease. Finally, the fluctuations in utilities of potential cooperation neighbors are delivered to the global networks, and the global benefits of all game players are influenced.

Besides, all game players are selfish and rational. They just want to increase their utilities by updating the suitable decision. Then, the related optimization problem of the proposed game is presented as follows:

$$P2:\ \max \quad U_n(a_n, a_{-n}),\ \ n \in \mathcal{N}. \tag{14}$$

B. Analysis of NE

Next, we will explore how to achieve continuous growth in the global system benefits when the utilities of local potential neighbors fluctuate periodically. Before the related analysis, we first give two important definitions, i.e., the definition of NE and EPG.

Definition 1 (Nash Equilibrium [48]): The joint cache content and transmission power strategy profile $a^* = (a_1^*, a_2^*, \ldots, a_N^*)$ is a NE of the multiuser content delivery game if and only if no game player, i.e., the consensus user, can improve its utilities unilaterally when updating its corresponding decision in the situation where others keep their decisions unchanged, i.e.,

$$U_n\left(a_n^*, a_{-n}^*\right) \geq U_n\left(a_n, a_{-n}^*\right), \quad \forall n \in \mathcal{N}, \quad \forall a_n \in A_n, a_n \neq {a_n}^* \tag{15}$$

where a_n^* is the best decision of consensus user n in the current situation, and a_{-n}^* is the corresponding best decision profile of others.

Definition 2 (Exact Potential Game [48]): Any proposed game is an EPG if and only if a unique potential function Φ exists corresponding to the utility function of the proposed game, which can be presented as follows:

$$\begin{aligned} &U_n(\bar{a}_n, a_{-n}) - U_n(a_n, a_{-n}) = \Phi(\bar{a}_n, a_{-n}) - \Phi(a_n, a_{-n}) \\ &\quad \forall n \in \mathcal{N} \quad \forall a_n \in A_n, \quad \forall \bar{a}_n \in A_n. \end{aligned} \tag{16}$$

Definition 1 explains the meaning of NE, and Definition 2 indicates the significance of the potential function. Meanwhile, it means that if we can prove the existence and find the corresponding potential function, our proposed game is an EPG.

Theorem 1: The proposed multiuser content delivery game is an EPG with at least one pure-strategy NE point. Meanwhile, the corresponding NE points consist of the optimal solution to the optimization problem $P1$.

Proof: In this section, we mainly discuss the existence of the potential function. Generally, the related potential function has a certain physical meaning, i.e., the aggregate throughput or aggregate interference. Inspired by the design thought, we define our potential function Φ, which is expressed as follows:

$$\Phi(a_n, a_{-n}) = \sum_{n\in\mathcal{N}} u_n(a_n, a_{-n}). \tag{17}$$

Equation (17) denotes the aggregate benefits of all consensus users, which is equal to (10), i.e., the global benefits. When any player n changes its decision unilaterally from a_n to a_n', then the change of the value in the potential function is presented as follows:

$$\begin{aligned} \Phi\left(a_n', a_{-n}\right) - \Phi(a_n, a_{-n}) = &\sum_{n\in\mathcal{N}} u_n\left(a_n', a_{-n}\right) \\ &- \sum_{n\in\mathcal{N}} u_n(a_n, a_{-n}). \end{aligned} \tag{18}$$

To a better analysis and understanding, we divide all consensus users into three categories: 1) the updating consensus user n; 2) the potential cooperation neighbors, i.e., $\mathcal{J}_n$; and 3) others, i.e., $\mathcal{N}\backslash\{\mathcal{J}_n \cup n\}$. Thus, (18) can be rewritten as follows:

$$\begin{aligned} &\Phi\left(a_n', a_{-n}\right) - \Phi(a_n, a_{-n}) \\ &\quad = \sum_{n\in\mathcal{N}} u_n(a_n', a_{-n}) - \sum_{n\in\mathcal{N}} u_n(a_n, a_{-n}) \\ &\quad = u_n(a_n', a_{-n}) + \sum_{i\in\mathcal{J}_n} u_i(a_i, a_{-i}') + \sum_{i\in\mathcal{N}\backslash\{\mathcal{J}_n\cup n\}} u_i(a_i, a_{-i}') \\ &\quad - u_n(a_n, a_{-n}) - \sum_{i\in\mathcal{J}_n} u_i(a_i, a_{-i}) - \sum_{i\in\mathcal{N}\backslash\{\mathcal{J}_n\cup n\}} u_i(a_i, a_{-i}). \end{aligned} \tag{19}$$

Considering the limited transmission power, consensus user n only influences the potential cooperation neighbors within its maximum communication range corresponding to the maximum transmission power. In other words, except for the potential cooperation neighbors, the benefits of other consensus users are the same with the previous benefits whatever whether player n updates its decision. Specifically, we can have

$$\sum_{i\in\mathcal{N}\backslash\{\mathcal{J}_n\cup n\}} u_i(a_i, a_{-i}) = \sum_{i\in\mathcal{N}\backslash\{\mathcal{J}_n\cup n\}} u_i\left(a'_i, a_{-i}\right). \tag{20}$$

Combined (19) with (20), we can obtain the following expression:

$$\begin{aligned} &\Phi\left(a_n', a_{-n}\right) - \Phi(a_n, a_{-n}) \\ &\quad = \sum_{n\in\mathcal{N}} u_n\left(a_n', a_{-n}\right) - \sum_{n\in\mathcal{N}} u_n(a_n, a_{-n}) \\ &\quad = u_n\left(a_n', a_{-n}\right) + \sum_{i\in\mathcal{J}_n} u_i\left(a_i, a_{-i}'\right) \\ &\quad - u_n(a_n, a_{-n}) - \sum_{i\in\mathcal{J}_n} u_i(a_i, a_{-i}). \end{aligned} \tag{21}$$

Next, when any consensus user n updates its decision from a_n to a_n', the change of the value in the corresponding utility function is presented as follows:

$$\begin{aligned} &U_n\left(a'_n, a_{-n}\right) - U_n(a_n, a_{-n}) \\ &\quad = u_n\left(a_n', a_{-n}\right) + \sum_{i\in J_n} u_i\left(a_i, a'_{-i}\right) \\ &\quad - u_n(a_n, a_{-n}) - \sum_{i\in J_n} u_i(a_i, a_{-i}) \\ &\quad = \Phi\left(a_n', a_{-n}\right) - \Phi(a_n, a_{-n}). \end{aligned} \tag{22}$$

Finally, we can find that the expression in Definition 2, i.e., (17), holds in our proposed game model. It means that in our game model, if there exists a player updates its decision, then the fluctuation trend of value in the potential function is equal to the change of value in the utility function. Thus, according to Definition 2, our proposed game is an EPG. Meanwhile, one of the important properties about the EPG game is that: there exists at least one pure-strategy NE point in any EPG game, and the corresponding NE points consist of the maximum value in the potential function. Then, Theorem 1 is proven. ■

IV. Context-Aware Content Delivery-Based Concurrent Better Reply Algorithm

In Section III, we design the corresponding game model to find a desirable solution to the optimization problem. Note that we merely prove the existence of NE points in our proposed game model in Section III. However, the detailed NE solution is not obtained. Note that it is difficult to solve the combinational problem for a center controller due to the high complexity and great calculation. Thus, it is necessary to design an effective distributed algorithm to find the solution to the problem. Then, in this section, we mainly discuss how to obtain the corresponding NE points of our game model.

A. Algorithm Design

In the game-theoretical framework, there exist many classical algorithms, e.g., better reply and best response, to obtain the NE of the corresponding game model. In this article, inspired by [49], we design the CCDCBR algorithm.

Compared with the traditional better reply, our proposed algorithm has innovative advantages as follows.

1) *Extend the Decision Variables of the Algorithm From 1-D Action to 2-D Action:* Generally, in a traditional better reply, the corresponding decision variable is 1-D action, e.g., the transmission power or cache content. However, in our proposed algorithm, we combine the transmission power with cache content and regard the combinational action as an individual decision.
2) *Have a Higher Convergence Rate:* In the distributed algorithm, the convergence rate plays an important role in performance. Specifically, when the number of players, i.e., consensus users, increases, it will bring a negative influence to the convergence of the algorithm. In order to solve this challenge, we improve the updating process from one-player updating to multiplayer updating, which greatly speeds up the convergence of our proposed algorithm theoretically.

As shown in Fig. 5, our proposed algorithm first initializes the initial decisions of all consensus users and the related simulation parameters. In other words, each consensus user randomly selects an available decision from their strategy space to provide service for requesters. Meanwhile, given the decisions of all consensus users, they estimate and sense the individual utility.

Next, to speed up the convergence of the proposed algorithm, multiple nonneighboring consensus users are selected to conduct the decision updating process. In this process, the corresponding users will randomly pick a new decision a_n' and sense the corresponding utility U_n'. Finally, these updating users will update their decisions according to the related utility, i.e., U_n and U_n'. The detailed information is presented in Algorithm 1.

In step 2 of the CCDCBR algorithm, multiple consensus users are selected. In order to achieve the selection of nonneighboring consensus users in reality, the contention

Algorithm 1: CCDCBR Algorithm

Initialization:

1) Initialize the initial decision of all consensus users, i.e., the random cache document and transmission power.

2) Set the related simulation parameters, e.g., the maximum iterations of the proposed algorithm and noise.

Repeat Iterations:

Step 1: All consensus users sense their utilities, i.e., U_n in current decisions, i.e., a_n, when they provide service for requesters.

Step 2: Multiple nonneighboring consensus users are selected to obtain the updating opportunity. The selected consensus users random select a new decision a_n' from their available strategy space.

Step 3: These updating users sense their utilities, i.e., U_n', over their new decisions. Meanwhile, players update their decisions by the following rule:

$$a_n(k+1) = \begin{cases} a_n', & \text{if } U_n(a_n, a_{-n}) > U_n(a_n', a_{-n}) \\ a_n(k), & \text{if } U_n(a_n, a_{-n}) \leq U_n(a_n', a_{-n}) \end{cases} \quad (23)$$

where $a_n(k+1)$ denotes the decision of consensus user n in the $(k+1)th$ iteration. Meanwhile, the joint decisions of others are unchanged.

End

The repeat iterations will stop and the algorithm will terminates when the maximum iteration is achieved or the utility remains stable during a period.

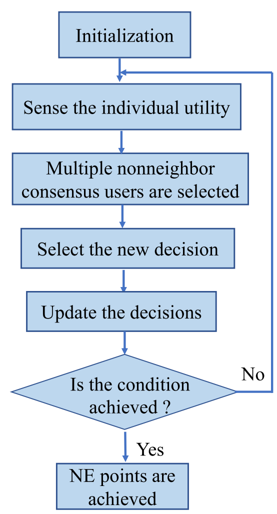

Fig. 5. Flowchart of the proposed algorithm.

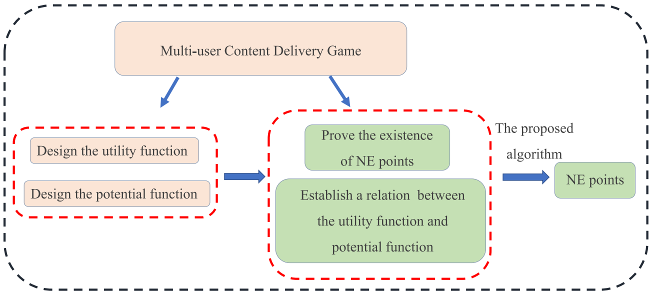

Fig. 6. Illustration of the proposed game framework.

mechanism is proposed. We assume that there exists a common control channel (CCC) available and all consensus users can work in CCC with corresponding 802.11 DCF-like contention mechanism [47]. The detailed description is given as follows.

1) A consensus user generates a backoff timer depending on uniform distribution in $[0, \tau_{\max}]$, where $\tau_{\max}$ represents the predetermined maximum backoff time.
2) Upon expiry of backoff timer, the consensus user sends a request to decision update (RTDU) packet in CCC to announce its intention for updating the cache content and transmission power.
3) All neighboring consensus users will freeze their backoff timers immediately and keep silent until the next iteration when hearing an RTDU before backoff timer expires.

B. Analysis of the Convergence and Complexity

Not like other distributed algorithms, e.g., best response, each player only conducts one comparison and avoids the global search in our proposed algorithm. Meanwhile, this updating mechanism can jump out of the trouble of local optimum and achieve the global optimum point with a high probability.

Theorem 2: The proposed CCDCBR algorithm can converge the corresponding pure-strategy NE points of our proposed multiuser content delivery game. The NE points can realize the local or global maximum of the system benefits.

Proof: As shown in Fig. 6, we propose the multiuser content delivery game model in Section III. Based on Definitions 1 and 2, we realize the proof of Theorem 1 where our proposed game model is an EPG and has at least one pure-strategy NE point. Specifically, there exists the same fluctuation trend between the utility function and the potential function, i.e., when the value in the utility function of any consensus user increases, so is the value in the potential function. Through this design, the utility function is associated with the potential function. Note that the utility function and the potential function denote the individual utility and global system benefits, respectively. In other words, when we optimize the utility of each consensus user, the aggregate system benefits increase simultaneously. Thus, through our proposed distributed algorithm, when the individual utility of each updating user increases step by step according to the finite improvement property (FIP) of game theory, then the global system benefits improve and finally converges to a maximum value in the potential function, which has the same physical meaning of (10). Therefore, the global system benefits are optimized locally or globally by our proposed CCDCBR algorithm. Accordingly, Theorem 2 is proved. ■

TABLE II
COMPLEXITY ANALYSIS OF THE PROPOSED ALGORITHM

Computation	Operation	Complexity
Eq. (9) and Eq. (13)	Sense the utility	$\mathcal{O}(C_1)$
—	Selection of updating users	$\mathcal{O}(C_2)$
Eq. (23)	Update the decision	$\mathcal{O}(C_3)$

Finally, we mainly discuss the computation complexity of the proposed algorithm as shown in Table II. Inspired by [50], for a better understanding, we denote N_{it} as the iteration times when the proposed algorithm terminates. The detailed analysis process is presented as follows.

1) In step 1, all consensus users need to sense their utilities. The complexity can be denoted as $\mathcal{O}(C_1)$, where C_1 is a small constant decided by (9) and (13).
2) In step 2, multiple nonneighboring consensus users will be selected by the proposed algorithm. Meanwhile, the complexity is $\mathcal{O}(C_2)$, where C_2 is a small constant due to the contention mechanism.
3) In step 3, the updating process involves the basic mathematical comparison between U_n and U_n', which is shown in (23). Accordingly, the complexity is $\mathcal{O}(C_3)$, where C_3 is a small constant related to the basic mathematical operation.

Therefore, the computation complexity of our proposed algorithm is $N_{it}(\mathcal{O}(C_1) + \mathcal{O}(C_2) + \mathcal{O}(C_3))$. Specifically, we introduce the concurrent operation in our proposed algorithm. The iteration times N_{it} are at a low level, which can be reflected by the simulation results in Section V. Meanwhile, the expression indicates that the computation complexity is independent of the number of consensus users. Thus, we can conclude that the computation complexity of our proposed algorithm is relatively low.

V. SIMULATION RESULTS AND DISCUSSION

A. Simulation Parameter Setting

In this section, related simulation results are presented to analyze the performance of the proposed game model and algorithm. Inspired by [41] and [51], simulation parameters are set as follows. As shown in Fig. 7, where the black dotted line denotes the potential cooperation neighbors, all helpers and requesters are distributed randomly in the network with 200×200 m^2. The number of helpers is $N = 5$ while the number of requesters with content demands is $M = 20$. Meanwhile, the fixed reward and variable reward factor are set to $R = 10^4$ and $r = 20$, respectively. The detailed parameter setting is presented in Table III.

TABLE III
SIMULATION PARAMETER SETTINGS

Parameter	Value
Popularity parameter	0.8
Area	$200 \times 200\text{m}^2$
Available transmission power	$0.1 \sim 0.6$ W
Path loss factor	3
Block size	$\mathcal{N}(200, 5)$
Poisson parameter	$\frac{1}{600}$
Delay factor	5×10^{-3}
Overhead per power	10^3
Overhead per bit	5×10^{-6}

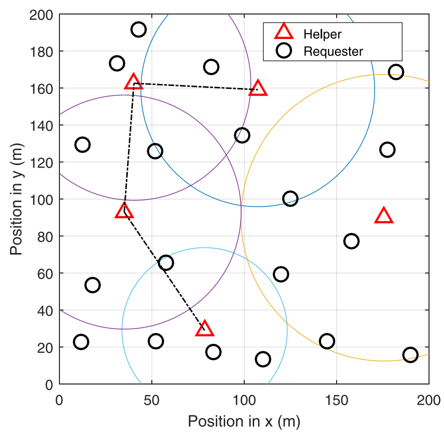

Fig. 7. Simulation network with 20 compute-intensive users, ten helpers, and one edge cloud located in the square area. The large solid circles represent the communication distance threshold.

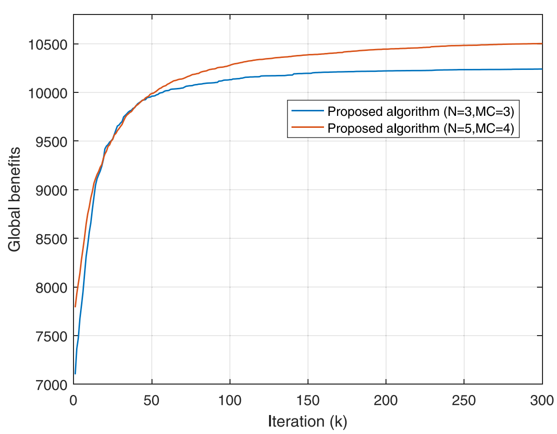

Fig. 8. Convergence of the proposed algorithms.

B. Convergence Behavior

In this section, we investigate the convergence behavior of the proposed algorithm. As shown in Fig. 8, we vary the number of helpers and the size of cache space to explore the convergence behavior under two different groups of simulation parameters, i.e., $N = 3, \text{MC} = 3$ and $N = 5, \text{MC} = 4$, in the system while keeping other simulation parameters unchanged. Meanwhile, the values in Fig. 8 are obtained through 500 independent trials where each network topology is different. When running in the condition of $N = 5, \text{MC} = 4$, the algorithm

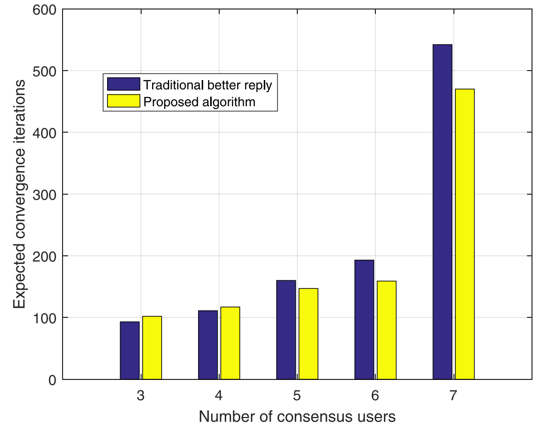

Fig. 9. Expected convergence iterations versus the number of helpers.

converges at a small iteration time, i.e., $k = 150$, which reflects a high convergence rate of the proposed algorithm.

Specifically, we compare the convergence speed of our proposed algorithm with the traditional better reply algorithm in Fig. 9. We vary the number of helpers from $N = 3$ to $N = 7$ and study the relationship between the expected convergence times and the number of helpers. As shown in this figure, the difference of the expected convergence times is small when the number of helpers is $N = 3$ or $N = 4$. However, with the increasing of the number of helpers, there exists a great gap gradually in the convergence speed. In particular, when the number of helpers is $N = 7$, the proposed algorithm not only realizes the convergence within a relatively low expected convergence times but also obtains a strong competitive advantage compared with the traditional better reply algorithm, which indicates the good scalability of the proposed algorithm.

C. Performance Evaluation

1) Cache Space: Fig. 10 presents the performance when varying the cache space of helpers. To highlight the superiority of the proposed algorithm, we introduce the following approaches as the comparison benchmark: the best NE, the worst NE, gene algorithm-based content delivery strategy (GA-CDS), and random selection algorithm. The corresponding approaches can be explained as follows.

1) *Best/Worst NE:* NE points are obtained from the best response algorithm. Then, we pick the best and worst solution of NE points from 500 independent trials as the best and worst NE.
2) *GA-CDS:* The traditional gene algorithm is introduced. To make it suitable for the multiuser 2-D decision, we encode the decision, including the transmission power and cache contents as gene segments, and then string all genes into one chromosome. Through the constant selection, crossover, and mutation, finally, a solution is obtained.
3) *Random Selection Algorithm:* Each helper randomly selects an available action from its strategy space. Given all random decisions of helpers, global benefits are achieved.

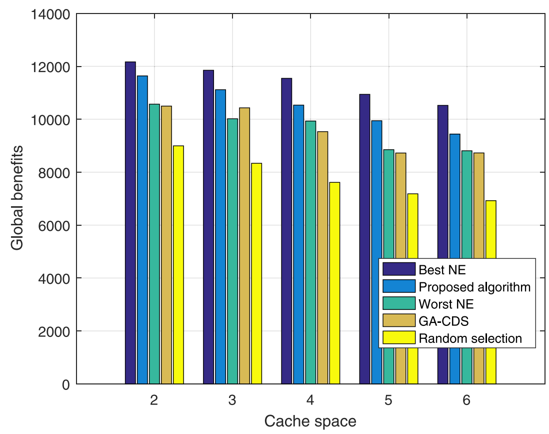

Fig. 10. Global benefits comparison when varying the cache space of helpers.

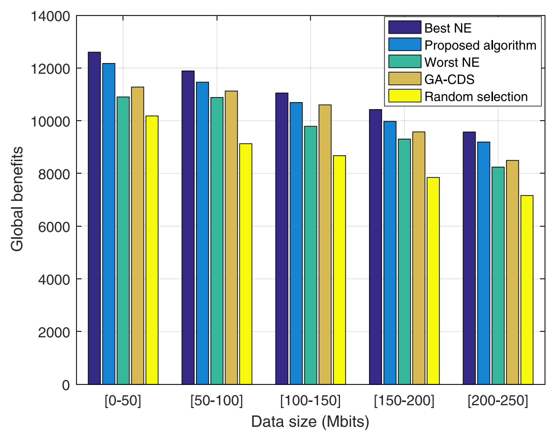

Fig. 11. Global benefits comparison when varying the data size of contents.

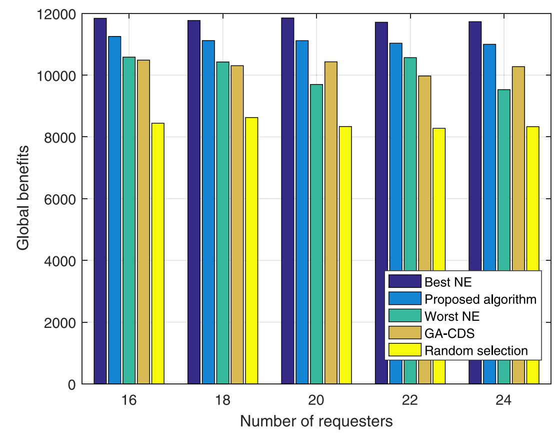

Fig. 12. Global benefits comparison when varying the number of requesters.

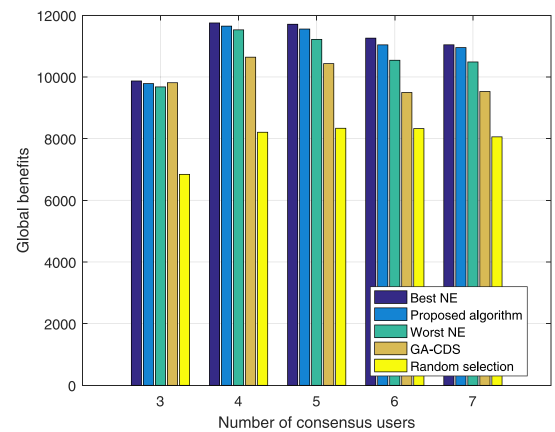

Fig. 13. Global benefits comparison when varying the number of helpers in a small edge cache network.

As shown in Fig. 10, the global benefits decrease with the growing cache space. It is because when helpers can cache more contents, the storage overhead rises significantly. Meanwhile, the performance of the proposed algorithm is between the best NE and the worst NE. The global benefits achieved by the proposed algorithm are higher than the random selection and GA-CDS.

2) Data Size: We investigate the performance of the proposed algorithm when varying the data size of each document in system library. Moreover, we set five different groups of data size from $D_f \in [0 \quad 50]$ Mbits to $D_f \in [200 \quad 250]$ Mbits. Similar to Fig. 10, the same decreasing trend is presented in Fig. 11. Although the global benefits decrease when the data size is growing as shown in Fig. 11, the proposed algorithm can still realize a higher performance than other approaches. In addition, the performance obtained by the proposed algorithm is near the best NE.

3) Number of Requesters: We study the influence of the number of requesters on the performance of the proposed algorithm. In the related simulation trials, we change the number of requesters from $M = 16$ to $M = 24$ while keeping other simulation parameters unchanged. As shown in Fig. 12, the global benefits achieved by all approaches are almost unchanged with the increasing number of requesters. It can be explained that when the number of requesters increases, helpers still complete mutually to attract more requesters. By adjusting their transmission power and cache contents in the proposed incentive mechanism, the number of requests who select to access the service of helper n, i.e., $|s_n|$, increases simultaneously with the growing questers. Consequently, the first term of (9), i.e., the reward of helpers allocated by the system, hardly changes due to $[|s_n|/M]$. Thus, the global benefits keep unchanged while the number of requesters is growing.

4) Number of Helpers: In Fig. 13, we explore the relationships between global benefits and the number of helpers. From the fluctuation trend of Fig. 13, we can find that the global benefits first increase when the number of helpers is from $N = 3$ to $N = 4$, then decrease when the number of helpers is from $N = 4$ to $N = 7$. The interesting phenomenon can be explained as follows: given the number of requesters, when there is a small number of helpers, the total content demands cannot be responded fully. Thus, when the number of responders, i.e., helpers, increases, the global benefits will rise due to the better performance. However, when there are enough helpers to provide service, the multiple players will compete with others. They adjust their decisions to attract more requesters with content demands to obtain higher benefits. Thus, when the number of helpers exceeds to a certain degree, each helper only serves limited requesters due to a fixed number of requesters.

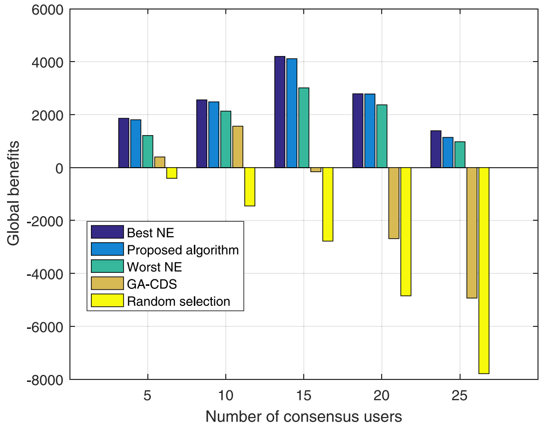

Fig. 14. Global benefits comparison when varying the number of helpers in a large edge cache network.

Taking the overheads of transmission power and storage, then the global benefits will decrease.

Finally, to verify the applicability of the relevant conclusions, we conduct the simulation with a larger number of samples. Given the large number of requesters, i.e., $M = 40$, we explore the performance when varying the number of helpers, i.e., consensus users, from $N = 5$ to $N = 20$. As shown in Fig. 14, it can be seen that the global benefits first increase and then decrease with the growing helpers. Note that the trend in Fig. 14 is the same as that in Fig. 13. Compared with the proposed algorithm, the performance achieved by the GA-CDS and random selection algorithm will decrease sharply when the number of samples increases. However, the proposed algorithms can still obtain a high global benefit. It validates the effectiveness for a large number of samples.

In summary, the fast convergence rate and good scalability of the proposed CCDCBR algorithm are presented by a series of simulation results. Specifically, the global benefits achieved by the proposed algorithm are higher than other approaches and near to the best NE, which is regarded as the optimal solution. Simulation results verify the validity and effectiveness of the proposed game model as well as the proposed CCDCBR algorithm.

VI. Conclusion

In this article, we investigated the multiuser content delivery problem in haptic communications. To overcome the selfishness of users and motivate them to share their local resources, we proposed a blockchain-based incentive mechanism. By jointly optimizing the cache content and transmission power, each helper can obtain the reward by responding the content demands of requesters. Then, the problem was formulated as the multiuser content delivery game with at least one pure-strategy NE point. Next, we proposed the distributed CCDCBR algorithm to achieve a desirable solution. Finally, the validity and effectiveness of the multiuser content delivery game as well as the CCDCBR algorithm were verified by the related simulation results.

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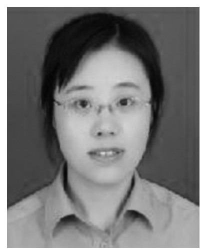

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