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Research Article

Algorithm Design for Sharing Orchestral Network Teaching Resources Using New Media Platform

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The new educational media platforms were introduced to address the problems related to sharing teaching content and promoting students' learning abilities. However, there are several issues with distributing educational resources on new media platforms, both globally and domestically. In terms of resources, teaching resources are scarce and individual and lack systematization, which affects the implementation and development of our orchestral education and teaching in new media. Regarding technology, there are currently vacancies in data linkage and exchange between different databases when the resource sharing platform is used and the existing system is in operation. The packet loss rate created by the existing technology is far too high. To address this problem, this paper designs a new platform as well as an algorithm, applies to online teaching resource distribution based on a new media platform, plans the teaching resource attributes of orchestral music majors, and studies the optimal solution for the resource sharing game model regarding load balancing and honesty allocation principles in a distributed scenario of heterogeneous networks. Experiments show that our strategy reduces network demand by a significant amount. The results made the designed algorithm applicable to be created, developed, and deployed practically.

1. Introduction

Network education must be supported by rich teaching resources constructed to deliver teaching content and facilitate students' learning knowledge. Modern network education must have rich teaching resources. Whether it is an international or domestic network college, the construction of teaching resources is the key to an efficient open network education; otherwise, a lack of online teaching resources or systems is bound to affect the development of available network education [1]. This open sharing approach of teaching resources was not adopted as it does not fulfill the development needs. The integration, release, and interactive sharing of teaching resources lacks integrity and scalability due to the continual development of information technology. Therefore, opening and sharing more high-quality course resources in the new media environment, such as online media, will undoubtedly provide more learning opportunities and better learning support services to members (learners) of the general society.

Traditional teaching resources rely on teachers' lecture notes and courseware. Changes in teachers or teaching materials may result in the original teaching resources not being passed on. All teachers can improve online course resources over time; good resources can be passed on, but new resources can also be contributed. In addition to face-to-face teaching, it opens a unique learning and communication channel for in-service students. They can review or review the knowledge taught on the teaching platform and complete various practical contents and tests online [2]. Students can also discuss online with all the lecturers or students of the course through the online platform for any professional knowledge problems that they do not understand or encounter in their work.

With the rapid development of computer technology, various new media have emerged; different education models and teaching methods have been adopted to improve the quality of education. However, each resource platform has its array and standards which lack unified management, making it impossible to achieve complete

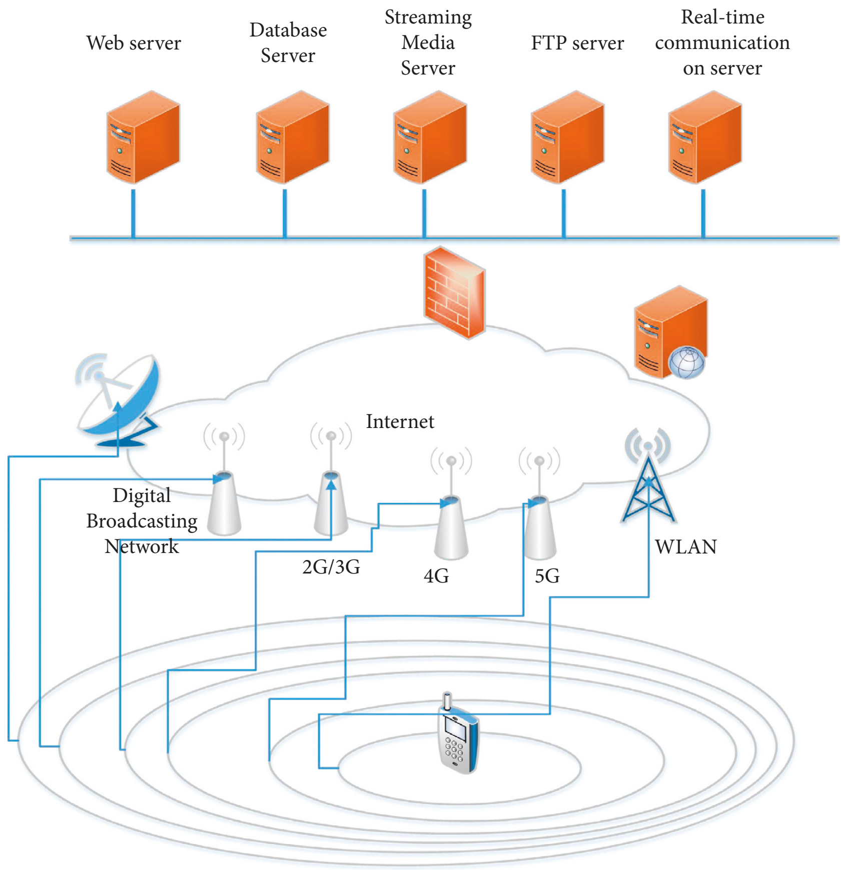

Figure 1: Heterogeneous wireless converged network environment.

resource sharing. From the technical point of view, different platforms use different computer equipment, network devices, and systems, forming a heterogeneous network. Compared with a single homogeneous network, heterogeneous networks have richer network services, more complex communication environments, and variations in network states and user requirements. Various network technologies are different in architecture, underlying access technologies, and implementation methods. This, coupled with the real-time and variable nature of user needs, poses a considerable challenge for efficient resource integration in heterogeneous networks. The traditional wireless resource management mechanism for single homogeneous networks requires various access technologies to work independently according to resource management algorithms. The only purpose is to provide quality of service guarantees for the user terminals participating in the network. In the case of heterogeneous multinetwork coexistence, various wireless access technologies differ significantly in transmission rate, stability, and mobility support by integrating access networks of different architectures. Mobile users should meet the quality-of-service requirements in different scenarios and improve the utilization of network spectrum resources.

Heterogeneous network wireless resource sharing management considers users' mobility, the diversity of network resources, service characteristics, network efficiency, and other factors. They assess each heterogeneous network and the users involved in the service as unique resources and treat the individual available resources as part of the group resources. The users can choose to rent or share all the group resources in the system so that the users and the network can actively participate in the coordinated allocation of wireless resources and establish a hybrid network resource management model [3]. The purpose is to utilize system-free resources better, expand network capacity, expand available network coverage, improve channel resource utilization and user service quality, adapt to variable network environments, and achieve a win-win situation for both networks and users. In the same way, heterogeneous network integration is the inevitable result of user operations, market demand, and technology development; as shown in Figure 1, heterogeneous networks coexist, forming a typical deployment of different access technologies [4]. Therefore, the user-provided resource sharing optimization technology studied in this paper is an optimized and upgraded solution for studying resource sharing management in heterogeneous networks. Its goal is to fix the flaws in existing research, enhance the benefits of heterogeneous network resource sharing, and provide users with more accessible and efficient options and services. Compared with traditional strategies such as system energy efficiency optimization, the research on user-provided resource sharing optimization algorithms focuses on using the following:

(i) User's resources to upgrade users to the network

(ii) Self-organizing to participate in the coordination and allocation of resources

(iii) Designing optimal resource sharing and allocation strategies from multiple perspectives to achieve better communication services

The rest of the research structures are as follows: Section 2 explains the related work done in this research paper. It is being followed by the methods in Section 3. Section 4 describes the implementation of the algorithm, while Section 5 describes the simulation results and analysis. Finally, the concluding remarks are explained in Section 6.

2. Related Work

The orchestral network was used to secure data sharing over several platforms for many years. The researchers have presented several related works to improve the smart and secure sharing of resources over different media, and these networks kept updating with time. The section is based on the existing literature pieces related to the work presented in this paper.

2.1. Current Situation of Teaching Resource Sharing. The teaching resources were not shared with proper and secure mediums in bygone days. But now, in this technologically advanced era, things are improving, and so are the networks. They perform efficiently and are better to use than the conventional ones. But there are still some challenges that need to be overcome. The following are the cons of the current teaching resources sharing networks.

2.1.1. Lack of Unified Standards for Curriculum Resources of New Media Platforms. The construction standards, specifications, and processes of curriculum resources of each new media platform are independent, forming their system. These standards are the essential networking standards required for any resource-sharing platform. The lack of unified teaching resources construction standards is equivalent to "shutting down" the construction of teaching resources with different standards and high-quality content, which cannot be shared on their platforms [5].

2.1.2. Lack of Unified Platform Management of Resources. For a long time, the lack of frequent communication and the construction of various curriculum resources on the new media platform has led to the homogenization of teaching resources, the lack of mutual recognition mechanisms and access channels for teaching resource management system, and the inability to share data information, along with the formation of data silos, resulting in the low utilization rate of resources and poor effect of resource sharing [5].

2.1.3. Lack of Unified Sharing Platform for Resources. Each new media platform has established its own digital teaching resource platform and lacks a unified sharing platform; teaching resources are not "open" and "shared," and teaching knowledge, teaching tools, and teaching methods are scattered [5].

Building a powerful platform for sharing curriculum resources on various new media platforms and making up for the shortage between resource platforms is one of the ways to develop high-quality education resources.

2.2. Resource Sharing Optimization Algorithms. Scholars have paid more and more attention to their research on resource-sharing optimization algorithms and have achieved good results. It summarizes the following optimization directions based on some critical literature research results.

2.2.1. Distributed Resource Sharing-Based Game Algorithm. Game theory has been a frequently used approach in resource-sharing research, especially in distributed scenarios of heterogeneous networks. It reduces the information collection of centralized optimizations and allows users to participate in the dynamic management of resources on their own. This enables the expansion of the network topology, improves system performance, and provides more flexible and convenient services. For example, model the interaction between operators and subscribers as a Steinberg game. Also, it examines the effects of operational costs, network coverage area, spatial reuse, and subscriber bidding on network and subscriber performance in the game algorithm. Hamouda (2022) investigated the energy-efficient spectrum sharing and power allocation problem for heterogeneous networks with cognitive capabilities. It formulates the energy-efficient resource allocation problem for heterogeneous cognitive wireless networks as a game-theoretic problem model [6].

The game utility function at each level considers energy efficiency and solves the optimal solution using the gradient iteration method. The literature [7] investigated distributed incentive models to encourage users to share available resources, optimize users' access to help, and share resources. The energy consumption is modeled using a virtual currency strategy as a Nash bargaining game model. The Nash optimal solution for resource sharing is obtained by solving the bargaining optimization problem. An auction approach has also been proposed in the literature [8], using dynamic spectrum access techniques to allocate spectrum resources for a secondary market, where spectrum resources can be sold or leased and shared, and dedicated users have the right to compete for resources.

This literature shows that the current research focuses on improving resource utilization and transmission energy consumption within heterogeneous networks by optimizing subcarrier and power allocation to effectively utilize users' idle resources and save download energy consumption. However, most studies ignore the initiative of users to participate in the resource-sharing game. They cannot avoid the selfish and greedy behaviors and malicious competition of users within the network, which will lead to an uneven load among networks and degrade the service performance. Therefore, the core of distributed resource sharing algorithm optimization is making users willing to participate in resource sharing services, ensuring relatively reasonable and efficient allocation of network resources, and controlling internetwork load and transmission energy consumption during the allocation process.

2.2.2. Analysis Based on Spectrum Heterogeneity. Most studies on resource sharing ignore the impact of spectrum variability on resource allocation. They always assume that the channel conditions among users are consistent and that all available channels are nondifferentiable concerning user services, and these assumptions are not ideal in practical scenarios with multiple access conditions in heterogeneous networks. In recent research results, researchers have considered the variability of channel carrier frequencies in spectrum allocation by studying the effect of carrier frequencies on user communication range and mutual interference relationships in a free-space transmission model with the same transmit power [9]. But without considering the variability among user channel demands, there are also studies on online auctions [10] that reflect the differences in user spectrum demands in the time domain but do not consider the difference in resource quality of the channels themselves.

It has been studied that load balancing methods are oriented to a heterogeneous spectrum, where the network side collects load information and maximizes the user throughput to derive the shunt probability, considering the resource transmission channel heterogeneity and expressing the static rate allocation problem of heterogeneous wireless access networks as a weighted bargaining game framework to balance the collaborative transmission traffic and control the network load [11]. It can be seen from the experimental results that although these algorithms based on spectrum heterogeneity analysis have some performance improvement, none of the single perspectives considering spectrum differences can achieve satisfactory resource allocation results. Most of such studies currently rely on a third-party platform (or central control) [12], a centralized control approach prone to selfish and greedy behavior. It can lead to model distortion, equilibrium misjudgment, and mechanism problems such as model distortion, equilibrium misjudgment, mechanism failure, and uncontrolled distribution. The core of current research is simultaneously considering the spectrum differences in resources and user demands, improving channel utilization and user service satisfaction, and designing flexible, fair, and practical resource sharing optimization strategies.

2.2.3. Based on Network Interference Coordination Analysis. The user devices of multilayer heterogeneous networks are more complex and diverse. The uncertainty of user mobility and network status makes the user resource sharing process subject to different degrees of network interference, causing changes in network resource status. This results in an uneven distribution of resources in the region and even causes network paralysis, which affects the reasonable fairness of resource sharing results. Therefore, network interference coordination algorithms have become a hot research topic in network resource sharing optimization technology.

Scholars have successively proposed some optimization schemes such as interference alignment, multipoint collaboration, and joint processing [13], all of which strongly rely on environmental information such as network resource states. Interference alignment is a linear precoding technique that attempts to align interfering signals in time, frequency, or space. Multipoint collaboration offers networking through several nodes. Joint processing guidelines provide a high-level approach to making archival material accessible in an open, efficient, and sustainable networking. Through experiments, [14] found that if the network state information is damaged during the resource sharing delivery, the system capacity will be limited even if the network terminals fully cooperate.

The expected results cannot be achieved. At the same time, when centralized processing is used, a large amount of network state information collection will burden the system, affect the transmission efficiency, cause network load imbalance, and improve the overall performance insignificantly. Therefore, to ensure that the advantages of heterogeneous hierarchical networks are brought into play, it is imperative to address the impact of user network state changes on resource allocation results during resource sharing within the system.

Some of them are the critical issues of such research, which raise several questions. How can the resource allocation strategy be adjusted based on real-time user network information? How to ensure different levels of requirements for each layer of the network? What studies the corresponding distributed reduction of information collection and centralized computing while reducing the impact of same-layer or cross-layer interference on user services and guaranteeing flexible, fair, and efficient resource sharing results? The paper addresses the above queries and presents an orchestral network algorithm to solve them.

3. Proposed Methodology

Distributed spectrum resource sharing service is a new dynamic resource management technology with low cost and high efficiency. In the distributed scenario, users can participate in the active management of resources on their own, which helps alleviate network congestion and meet the communication needs of users. The distributed spectrum resource sharing service aims to actively encourage users to share idle network resources, which will be rational and efficient in resource allocation and management according to different users' needs; meanwhile, the game theory was studied and found that it is a sensible conflict and cooperation, and the mathematical model is well suited to solve the problem of greed and selfishness among users in the process of spectrum resource sharing collaboration and competition. Game theory is the dominant resource-sharing research approach [15]. Through the study of distributed resource sharing game algorithms in the literature, a distributed spectrum resource sharing service based on game theory was found. It is a well-designed incentive mechanism

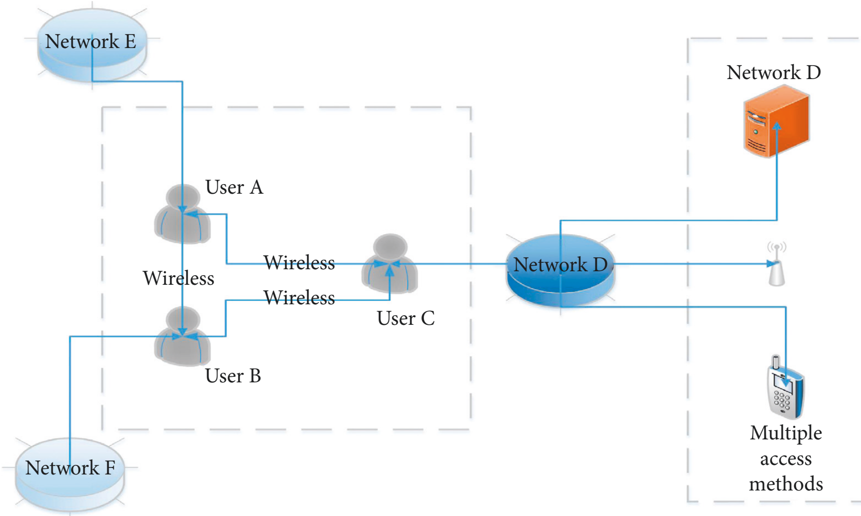

Figure 2: Network architectural model.

for improving users' participation in the service plan to ensure the honesty and reliability of information sharing among users while avoiding selfish greed and malicious competition among users within the network. The service performance is guaranteed. Therefore, in the distributed game-theory-based spectrum sharing algorithm's optimization process, the network resource utilization should be ensured, and the incentive mechanism should be improved to enhance user participation. The network topology needed to be expanded and further study the utility of the network and users affected by the load change to avoid the uneven distribution of resources and control of load balance.

Our work has been extended to a distributed spectrum resource sharing algorithm optimization problem based on game theory. The main optimization goal is to design incentive mechanisms to avoid selfish and malicious competition among users while enhancing their initiative to participate in the service. On the other hand, study the distributed resource sharing game algorithm that reasonably controls the network load while safeguarding user demand and network performance. Firstly, the spectrum resources among users as a new network access method, users upgrade to the network, introduce the virtual currency system, and consider the user utility and transmission energy consumption to establish a mathematical game model for network selection of mixed resources. At the same time, the concept of the security deposit is proposed in the game process, a new security deposit incentive mechanism is designed, the relationship between load and overhead is modeled, and the input and output of virtual currency are used to reflect the network load pressure. It can prevent users from selfishly competing maliciously, considering the independent download situation and comparing and analyzing the impact of this algorithm on overhead, energy consumption, resource utility, and network load changes.

3.1. Network Architectural Model. Consider a heterogeneous wireless network scenario in a cellular coverage area where a collection of mobile users represents service providers involved in resource sharing, capable of upgrading to potential users of the network; they may interact directly with one another via a mesh network N, where wireless is a collection of directed links connected by access technologies such as Wi-Fi and Bluetooth [16]. Mesh topology is a type of networking where all nodes cooperate to distribute data. This topology was developed 30+ years ago for military applications, but it is typically used for home automation, smart HVAC control, and smart buildings today. The selection is based on its effective performance and security over the other networks. The network architectural model is shown in Figure 2.

In each phase, users can take one or more roles: a client node (consuming data), a relay node (routing data to other users), or a gateway node (downloading data directly from the Internet). The utility function B is a positive increasing convex function of the amount of data downloaded or relayed. The utility function's convexity models the user's change in marginal benefit satisfaction because of data consumption. Depending on their demands and the network environment, various users have varied utility functions. The utility is proportional to the quantity of data downloaded or transmitted at first, but it saturates once the maximum predicted data or corresponding time session is reached.

A user requirement is first defined to include a demand metric, a download budget, and the expected number of resources required. Demand metrics include expected throughput t, delay d, and jitter value r [17]. The utility function can be expressed as a function of the quantities of a bundle of goods or services, often denoted as $U(X_1, X_2, X_3$, and $X_n)$. Utility functions combine performance criteria such as bandwidth, cost, and signal strength. Its mathematical relation with ω is as follows:

$$B \propto \left(\frac{\omega_t t}{\omega_d d \omega_r r}\right), \quad (1)$$

where ω is used to reflect the user's sensitivity to the demand metrics [18]. This sensitivity is determined by both the demand metrics and the current network state. The more significant the gap between the demand and current network metrics, the higher its value will be.

Take the service provided by any node i to node $m(m \in \alpha)$ in the network. $y_i \geq 0$: denotes the amount of data downloaded directly from the Internet by user i. $x_{ij} \geq 0$: the amount of data delivered to neighbor j by user i as a relay share. The download matrix: $y = (y_i^m \geq 0\colon i \in \alpha, m \in \alpha)$. Routing relay matrix: $x = (x_{ij}^m \geq 0\colon (i,j) \in \alpha, m \in \alpha)$.

A traffic balance equation exists for data transmitted for node m [19]: the total data sum of any node i relaying or downloading for m is equal to the amount of data output to the next node, i.e., the following equation holds:

$$\sum_{j \in \mathrm{In}(i)} x_{ji}^m + y_i^m = \sum_{j \in \mathrm{Out}(i)} x_{ij}^m, \forall i, m \in \alpha, i \neq m. \tag{2}$$

Each link can only handle a certain amount of data. The amount of all relayed and downloaded data at any node cannot exceed the maximum capacity. There exist the constraints that are

$$\begin{aligned} &\sum_{m \in \alpha} x_{ij}^m \leq A_{ij}, \forall (i,j) \in \beta, \\ &\sum_{m \in \alpha} y_i^m \leq A_{0i}, \forall (i,j) \in \alpha. \end{aligned} \tag{3}$$

At the same time, the system has an energy consumption relationship model as follows:

$$e_i = \sum_{j \in \mathrm{Out}(i)} e_{ij} \sum_{m \in \alpha} x_{ij}^m + \sum_{j \in \mathrm{In}(i)} e_{ji} \sum_{m \in \alpha} x_{ij}^m + e_{0i} \sum_{m \in \alpha} y_i^m, e_i \leq E_i. \tag{4}$$

E_i reflects each user's energy budget, and various mobile devices may consume energy in different ways. Some users, for example, may be willing to expend nearly their whole energy allotment at this time, but others may choose to consume less energy. As a result, we present C, a strictly convex, positive, and user-specific energy consumption preference function. When the user's energy budget is exhausted, its value tends to infinity and is expressed as follows:

$$C_i(e_i) = \frac{\delta_i}{(E_i - e_i)}. \tag{5}$$

$\delta_i \in [0,1]$ reflects the sensitivity of user i to energy consumption.

3.2. Analyzing the Problem. Let Q denote the benefit of user i's participation in resource-sharing. Benefit = utility function $*$ amount of data demanded by user i (download + relay)-overhead of downloading data directly from the Internet (relaying for other users)-energy cost of data transmission. The following equation gives the objective function:

$$Q_i(x_i, x_{-i}, y_i) = B_i\left(y_i^{(i)} + \sum_{j \in \mathrm{In}(i)} x_{ji}^{(i)}\right) - \ell_i \sum_{m \in \alpha} y_i^m - C_i(e_i), \tag{6}$$

where $y_i = (y_i^m\colon m \in \alpha)$represents the download vector; $x_i = (x_{ij}^m\colon j \in \mathrm{Out}(i), m \in \alpha)$ is the routing vector, where user i transmits data $x_{-i} = (x_{ji}^m\colon j \in \mathrm{In}(i), m \in \alpha)$ to the outside; and it is the data transmitted from the outside to user i. From (6), as $y_i^{(i)}$ increases, user i's own utility increases. However, the download overhead and energy cost increases simultaneously, so, the overall benefit of i may not rise. On the other hand, the widespread use of user i decreases as the amount of data downloaded on behalf of further user m increases, inversely proportional to the energy consumption of routes to downstream neighbors. There is no incentive to relay or download data for other user m unless the current user is compensated. The current x_{-i} contains two parts: the amount of data required to satisfy the user's utility (determined before the game); and the second part is the amount of data relayed for another user m. This part is not defined in advance and will be adjusted according to the compensation measures given by another user m. The user does not decide this process alone, but it is an interuser game process.

An incentive mechanism introduces a virtual currency system to categorize and price resources while increasing users' motivation to share and relay resources, determining which users should share how many resources, maximizing throughput, and ensuring load balancing. The incentive mechanism can guide how different users share resources and how to compensate users, which is called the guaranteed money incentive mechanism.

Some traditional algorithms like the Brute Force algorithm, recursive algorithm, and more, only include a fixed incentive and do not adjust the resource allocation according to the situation of each node, which may lead to greedy and selfish behavior of some nodes that may overload the nodes because they have more resources than the overall benefit of sharing resources. In the process of resource gaming among users, each node in the system requires flexible resource allocation under the influence of the security deposit mechanism, which improves the incentive mechanism and enhances flexible allocation, making the load of each node in the system (that is defined as the load equal to the ratio of the current number of resources held by the user to the maximum transmission carrying capacity of its link) moderate.

However, there are two caveats in this game process:

(1) The current user may not be able to directly reward other users by providing similar relay or download services during the period when they are receiving services from other users (i.e., unwilling to help).

(2) For the above two cases, it is necessary to consider both the gain when downloading independently, i.e., the user will not download other user data ($y_i^m = 0, \forall m \neq i$), and the best download policy when downloading independently does not participate in resource sharing. It does not receive neighboring relay delivery data ($x_{ij}^m = 0, \forall j \in \mathrm{Out}(i), x_{ji}^m = 0, \forall j \in \mathrm{In}(i), \forall m \in \alpha$). Currently, the objective function is $\max_{0 \leq y_i^{(i)} \leq A_{0i}} B_i(y_i^{(i)} - \ell_i y_i^{(i)} - C_i(y_i^{(i)}))$. The aim is strictly concave, while the collection of nonempty constraints is compact and convex. It has an independent solution, denoted as Q_s^i, and where s indicates independence, its performance will be used as a benchmark for comparison.

A virtual currency system is introduced to encourage users to participate in resource sharing. Even if they are unable to engage in routing or downloading services, users pay to use the service and collaborate. Users can still benefit from sharing communication resources flexibly through a bargaining process, even if they have no communication needs. $Z_{ji}^m \geq 0$ denotes the price paid by user i to user j for data delivered over the link $j \longrightarrow i$; $Z_{ji}^m \geq 0, j \in \mathrm{Out}(i), i \longrightarrow j$ data commodity price $Z_i = (Z_{ji}^m\colon j \in \mathrm{In}(i), m \in \alpha)$; price matrix $Z_{-i} = (Z_{ij}^m\colon j \in \mathrm{Out}(i), m \in \alpha)$; each user's security deposit budget $G_i \geq 0$.

The amount of virtual money of the user at the end of the game

$$K_i(z_i, z_{-i}) = \beta_i\left((1-\gamma_i)G_i + \sum_{m\in\alpha}\sum_{j\in\mathrm{Out}(i)} z_{ij}^m - \sum_{m\in\alpha}\sum_{j\in\mathrm{In}(i)} z_{ji}^m\right), \tag{7}$$

where the parameter $\beta_i \geq 0$ captures the importance of virtual currency to user i, i.e., it reflects her expectation of utilizing virtual currency in the future. For example, a user who does not intend to participate in the service does not place much importance on virtual currency, and the corresponding β_i will be close to 0. Of course, in this paper, the higher the user's desire to share, the higher will be the monetary gain. In this paper, the γ_i is defined as the discount on the security deposit to be paid before receiving the resource and the value of virtual currency to reflect the user's desire to participate in the shared resource service β_i.

3.3. Security Deposit (Pricing) Incentive Mechanism. Users who apply for resources give the corresponding security deposit to the resource provider according to the number of resources. When the resource provider becomes the user to send resource requests in the next transaction, they can pay less security deposit accordingly to the services provided. Encourage users to take the initiative to share resources and get resources with lower investment.

The desire to β_i is related to two following factors:

(1) The security deposit offer received by the sharing network
(2) The network loads

$$\beta_i = \frac{\gamma_i}{\left(1-\left(x_{-i}^{(i)} + y_i^{(i)}\right)/A_i\right)}. \tag{8}$$

where x_{-i} is the number of resources acquired by user i, and x_i is the number of resources shared.

The security deposit offer received by the network after sharing the resources γ_i:

$$\gamma_i = \kappa \times \frac{x_{i-}^m}{x_{-i}^{(i)} + y_i^{(i)}}, \tag{9}$$

where k is proportional to the amount of shared relay resources and inversely proportional to the amount of occupied resources, with κ being the preference scale, depending on the efficiency of the resource sharing system [20], after calculating the sharing desire, β_i is a strictly concave, positive function with respect to the load, when the load within the network approaches the limit, the sharing desire will tend to be infinite, which can both enhance the motivation of users to share resources and alleviate the problem of high network load due to the selfish greediness of users.

4. Implementation of the Algorithm

The orchestral network-based algorithm computed from the equations discussed in the previous sections will be implemented in this section. The implementation will be on the software, for which the required code is presented under the Algorithm 1 label. Some equations and mathematical constraints are discussed as follows.

The bargaining problem can be expressed as follows:

$$\underset{x,y,z}{Max} \sum_{i\in\alpha} \log\left(Q_i(x_i, x_{-i}, y_i) + K_i(z_i, z_{-i}) - Q_i^s - \beta_i G_i\right). \tag{10}$$

Flow balance constraint

$$\sum_{j\in\mathrm{In}(i)} x_{ji}^m + y_i^m = \sum_{j\in\mathrm{Out}(i)} x_{ij}^m, \forall i, m \in \alpha, i \neq m. \tag{11}$$

Link capacity constraint

$$\begin{aligned}&\sum_{m\in\alpha} x_{ij}^m \leq A_{ij}, \forall (i,j) \in \beta,\\ &\sum_{m\in\alpha} y_i^m \leq A_{0i}, \forall i \in \alpha.\end{aligned} \tag{12}$$

Virtual currency deficit constraint

$$\sum_{m\in\alpha}\sum_{j\in\mathrm{In}(i)} z_{ji}^m - \sum_{m\in\alpha}\sum_{j\in\mathrm{Out}(i)} z_{ij}^m \leq (1-\gamma_i)G_i, \forall i \in \alpha. \tag{13}$$

Feasibility constraint

$$Q_i(x_i, x_{-i}, y_i) + K(z_i, z_{-i}) \geq Q_i^s + \beta_i G_i, \forall i \in \alpha. \tag{14}$$

There is no reduction in user revenue by participating in resource sharing, assuming that all users are motivated to participate in the resource sharing procedure at each period, guaranteed by the virtual currency system, particularly the guarantee γ.

$$x_{ij}^m \geq 0, y_i^m \geq 0, 0 \leq z_{ij}^m \leq W, \forall i, j, m \in \alpha. \tag{15}$$

W is the network payment constraint, and the point of divergence of the gain is the sum of the independent performance Q_i^s achievable by the user and the standardized virtual currency $\beta_i G_i$ initially owned without participation in resource sharing.

This negotiating dilemma has a single best answer. Proof: since the objective function is a combination of (strictly) concave functions, it is purely concave and, in addition, the constraint set is tight, convex, and nonempty, while the logarithmic parameters are nonzero. The objective is a convex function if minimizing or a concave function if maximizing. Therefore, this problem always has a unique solution.

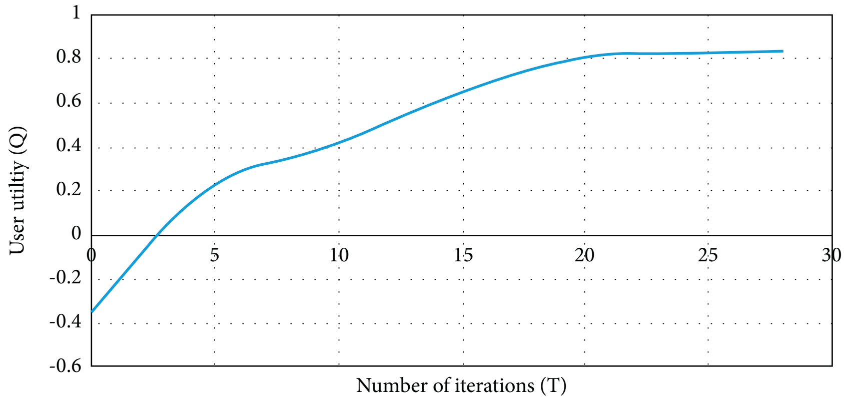

FIGURE 3: Distributed resource sharing game user utility change curve.

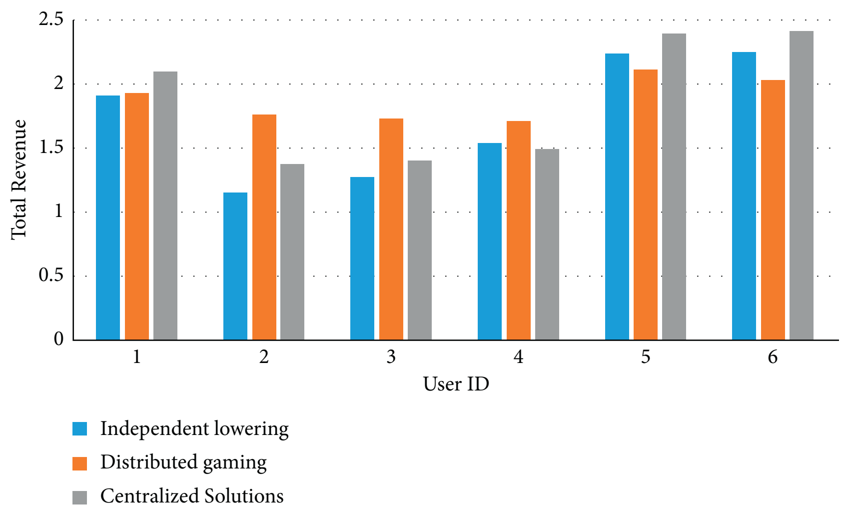

FIGURE 4: Comparison of the distributed game, centralized scheme, and independent download.

4.1. Distributed Game Algorithm Solution Idea. There are two issues in using a distributed approach to solve the bargaining problem. First, the constraints are coupled with the decision variables of different users, i.e., each user's routing decision should consider the capacity constraints of its neighboring nodes; second, the objective function is coupled, i.e., the objective log component corresponding to each user I is influenced by its neighbors' choice variables. The auxiliary variables are called artificial variables and are different from surplus ones. They are used preferably on the global variables as they perform well (proven experimentally). The transformed problem is associated only with the constraints and can be solved by the original pairwise Lagrangian decomposition.

Solution: introduction of auxiliary variables matrix. Each user can choose their own download, routing, and payment factors, and their one-hop neighbors utilize auxiliary variables to make routing and payment decisions. As a result, the variables may be aggregated for each user, requiring each user to make just local selections. Relaxing the constraint introduces Lagrange multipliers separately. Defining the Lagrangian function as

$$\begin{aligned} L = &\sum_{i\in\alpha}\left(\log\left(Q_i\left(x_i,\xi_i,y_i\right)+K\left(z_i,\sigma_i\right)-Q_i^s-\beta_i G_i\right)\right) \\ &+\sum_{m\in\alpha}\lambda_i^m\left(\sum_{j\in\mathrm{In}(i)}x_{ji}^m+y_i^m-\sum_{j\in\mathrm{Out}(i)}x_{ij}^m\right) \\ &+\sum_{m\in\alpha}\sum_{j\in\mathrm{In}(i)}\mu_{ji}^m\left(\xi_{ji}^m-x_{ji}^m\right) \\ &+\sum_{m\in\alpha}\sum_{j\in\mathrm{Out}(i)}\pi_{ij}^m\left(\sigma_{ij}^m-z_{ij}^m\right) \\ &-\rho_i\left(\sum_{m\in\alpha}\sum_{j\in\mathrm{In}(i)}z_{ji}^m-\left(1-\gamma_i\right)G_i-\sum_{m\in\alpha}\sum_{j\in\mathrm{Out}(i)}z_{ij}^m\right). \end{aligned} \tag{16}$$

After simplification, the gradient is computed using the original variables and updated to obtain the Lagrange multiplier iteration formula.

$$\mu_{ji}^{m(t+1)}=\mu_{ji}^{mt}+o^t\times\left(\xi_{ji}^{mt}-x_{ji}^{mt}\right). \tag{17}$$

$$\pi_{ij}^{m(t+1)}=\pi_{ij}^{mt}+o^t\times\left(\sigma_{ij}^{mt}-z_{ij}^{mt}\right). \tag{18}$$

$$\lambda_i^{m(t+1)}=\lambda_i^{mt}+o^t\times\left(\sum_{j\in\mathrm{In}(i)}x_{ji}^{mt}-\sum_{j\in\mathrm{Out}(i)}x_{ij}^{mt}+y_i^{mt}\right). \tag{19}$$

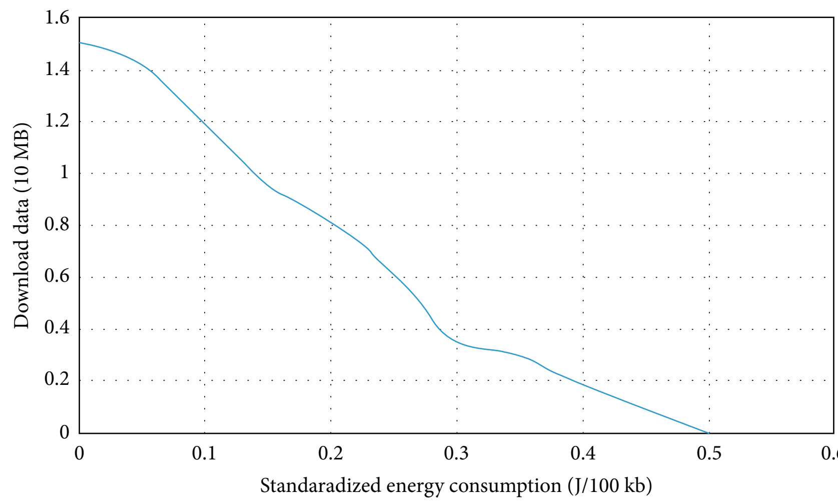

Figure 5: Wi-Fi user download access to resources versus energy consumption.

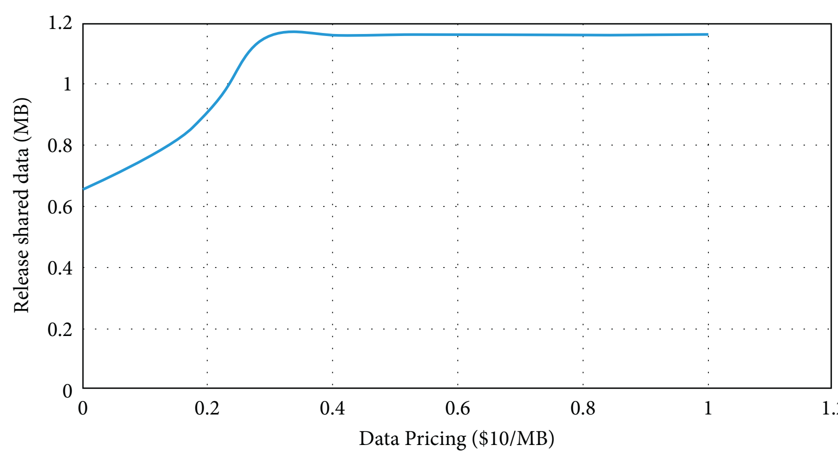

Figure 6: Relationship between the amount of data shared by 4G users and the pricing of data resources.

$$\rho_i^{m(t+1)} = \rho_i^{mt} + o^t \times \left(\sum_{j \in \mathrm{Out}(i)} z_{ji}^{mt} - \sum_{j \in \mathrm{In}(i)} z_{ij}^{mt} + \left(1 - \frac{\kappa * \sum_{j \in \mathrm{Out}(i)} x_{ij}^{mt}}{y_i^i + \sum_{j \in \mathrm{In}(i)} x_{ji}^i} \right) \right). \tag{20}$$

where $o^{(t)} \geq 0$ is the correctly chosen step in iteration t. In the following cycle, each user transfers the updated pairwise variables to a neighbor, who will use them to optimize the main variables. The goal of this bargaining issue is strictly concave, while the constraints are closed, nonempty, and convex. Thus, the algorithm converges to an optimal solution if the step function $o^{(t)}$ is correctly chosen and the gradient used in the multiplier iteration formulation is bounded. The optimal choice of the iteration step must be obtained in iterative experiments [21]. The algorithm allows joint decision-making by the participating users, and global information unification is achieved by interacting information from the network and user sides.

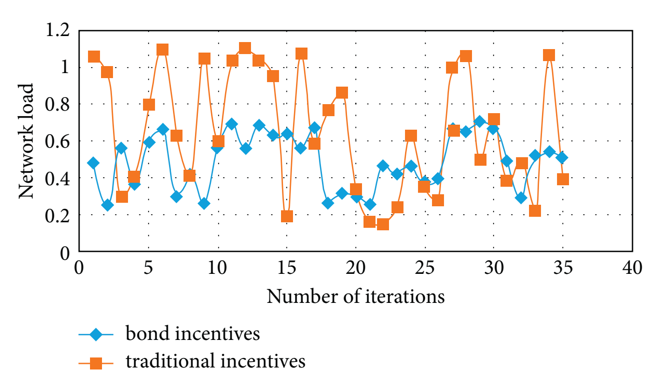

Figure 7: Comparison of a load of bond incentives with traditional incentives.

5. Simulation Results and Analysis

In this section, a basic system setup is considered, assuming the presence of three access methods in the network: mobile

Output x^*, y^*, z^*
$t = 0$
Initialize x^*, y^*, z^*
convex flag conv_flag = 0
While conv_flag = 0 do
  for $i = 1$: I do
    for $j = 1$; $j <= I$; do
      Calculate equations (17)–(20) to get $\lambda_i^{(t+1)}, \rho_i^{(t+1)}, \mu_i^{(t+1)}, \pi_i^{(t+1)}$
    End
  End
  if $(|\lambda_i^{(t+1)} - \lambda_i^{(t)}| < \varepsilon \text{and} |\rho_i^{(t+1)} - \rho_i^{(t)}| < \varepsilon \text{and} |\mu_i^{(t+1)} - \mu_i^{(t)}| < \varepsilon \text{and} |\pi_i^{(t+1)} - \pi_i^{(t)}| < \varepsilon)$
  conv_flag = 1
  End
End

Algorithm 1: Distributed game algorithm execution process.

4G, LTE, and Wi-Fi, and the system parameters follow the relevant experimental study [22]. For this study, a group of 6 users, randomly placed in a geographical area, is considered to study the interaction of their resource scheduling during a defined time. The network bandwidth of each user depends on whether the mobile 4G, LTE, or Wi-Fi connection is used, with an average speed of 96 Mbps for 4G networks, 50 Mbps for LTE, and 18 Mbps for Wi-Fi. In addition, in practice, the interference and congestion in the network affect the adequate capacity of the network, i.e., assuming direct communication between users using Wi-Fi, the communication rate between two users decreases with their Euclidean distance. When the distance exceeds a certain distance, the rate is zero. The maximum amount of data transmitted by a link within the network is denoted by A_{ij}.

The amount of energy needed for data transmission by mobile devices is related to the data size and power level; the energy consumption is also affected by channel conditions and transmission rate. Typically, Wi-Fi transmission energy consumption (per Mbyte) is less than LTE transmission and 4G, assuming the average energy consumption of a user with 4G Internet access $e_{0i} = (20J/M\text{Byte})$, an LTE connection $e_{0i} = (4.8J/M\text{Byte})$, and a Wi-Fi connection $e_{0i} = (2.80J/M\text{Byte})$. Also, for Wi-Fi links, it is assumed that the energy consumption per Mbyte increases with distance (Lv and Ke, 2020).

Each user has a logarithmic utility function $B_i = a_i \log(1 + y_i^{(i)} + \sum_{j\in \text{In}(i)} x_{ji}^{(i)})$ that satisfies the principle of diminishing marginal returns, with parameter a capturing the communication needs of different users. Also, the scale of the guaranteed preference in the virtual currency sharing desire β_i is set to 0.3. The final data pricing depends on prices in different regions and is set for users with unlimited cellular data plans $\ell_i = 0$. An initial virtual currency security deposit budget of 1 is established for each user; finally, the algorithm is given to jump out the conditional value $\varepsilon = 0.01$.

First, it is considered user access, such that user 1 has LTE connectivity, user 2 does not have any Internet access, users 3 and 4 have 4G access, and users 5 and 6 have Wi-Fi access. The users' network capacity, energy consumption, and pricing parameters are as above. In this experiment, we first record the change of an individual user (4G) utility. The user utility grows gradually through the process of a distributed spectrum resource sharing game among users, and the utility value smoothly tends to the maximum value at the end of the game (as shown in Figure 3); second, we compare the individual user. The total benefit is given as the average of more than 100 trials at different locations and distances between users (as shown in Figure 4). We observe that the distributed gaming solution improves the total user benefit by about 10% relative to the independent download solution. In contrast, the centralized solution may reduce the total benefit for some users compared to the independent solution, reflecting the fairness advantage of distributed gaming.

Next, we simulate a scenario where 4G and Wi-Fi users choose to download and share resources. When Wi-Fi links are congested and 4G access costs are low, downloading resources is more attractive (Figure 5). As the energy consumption of 4G users to transmit data to Wi-Fi users increases, Wi-Fi users' downloads to obtain data decreases. On the other hand, when 4G users have sufficient link resources and face load and guarantee money pressure, users will be more inclined to share data resources (as shown in Figure 6). After the game between users about resources and pricing, users' share of resources will stabilize relative to resource pricing because 4G data prices increase. Total budget constraints cannot compensate for Wi-Fi users' virtual money; 4G users will not send data to Wi-Fi users to send data; and the data traffic in the network tends to be balanced.

We also consider a single user in a heterogeneous network scenario and compare the impact of the traditional incentive mechanism scheme with this paper's security deposit incentive mechanism scheme on user load balancing (as shown in Figure 7). We record the network load pressure at each iteration during the resource sharing game, where t is the number of iterations and $S = ((x_{-i}^{(i)} + y_i^{(i)})/A_i)$ is the defined network load. We can see that after adopting the security deposit incentive mechanism, the network load fluctuates significantly less than the traditional incentive mechanism. The variation is considerably smaller than that of the conventional incentive mechanism.

The conventional incentive mechanism may exceed the maximum capacity of a single network link in the game process, which may easily lead to network paralysis. In contrast, the distributed game based on the security deposit incentive mechanism controls the network's load balance, avoids selfish and malicious competition among users, and ensures its fairness principle based on maximizing the overall benefits of the network. Based on the results, it can be concluded that the system can be practically implemented and deployed accordingly.

6. Conclusion

This research investigates the best solution of the resource sharing game model in terms of load balancing and the honesty allocation principle in a heterogeneous network dispersed scenario using symphonic resource sharing under new media. Firstly, the user utility and transmission energy consumption models in the heterogeneous network scenario are established, the optimization problem of the security deposit incentive mechanism is proposed for the drawbacks of the traditional incentive mechanism, the virtual currency system is introduced, and the relationship between network load and overhead is modeled. Then the objective function of maximizing user benefits is solved using theories such as convex optimization and decoupling auxiliary variables. Finally, it can be proved through numerical simulations that the distributed resource sharing game algorithm based on the security deposit incentive mechanism can improve the user utility. At the same time, the gain is higher than the independent download and is more rational than the centralized operation allocation scheme. The performance comparison with the traditional incentive mechanism achieves a good improvement in the network load. It can avoid the load pressure difference caused by greedy and selfish behavior among users. It can prevent excessive load pressure differences or even network paralysis caused by greedy and selfish behavior among users, effectively control network load balance, and flexibly adjust the resource allocation strategy.

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 he has no conflicts of interest.

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