Blockchain-Based Dynamic Spectrum Sharing for Service-Centric 6G Networks: An Evolutionary Approach

Kun Yan, *Graduate Student Member, IEEE*, Wenping Ma, *Member, IEEE*, Shaohui Sun, *Member, IEEE*, and Weiwei Wang, *Graduate Student Member, IEEE*

***Abstract*—The ongoing evolution of network technology and increasing service requirements have positioned spectrum resource management and exploration as a central focus in current and future network research. To accommodate the diverse services anticipated in future 6G networks, dynamic spectrum sharing (DSS) must be implemented across multiple factors to optimize the utilization of existing resources, in addition to exploring new frequency bands. This article proposes BEE, a two-stage, sharding blockchain-based DSS mechanism designed for service-centric 6G networks operating across various frequency bands. In the first stage, BEE utilizes an improved evolutionary algorithm to establish a fine-grained spectrum allocation scheme, facilitating dynamic spectrum management between providers and requesters. In the second stage, BEE offers price-guided spectrum trading for operators and users, utilizing evolutionary game theory to maximize the number of served users. The security analysis demonstrates that BEE provides a secure and reliable platform for DSS. Furthermore, simulation results demonstrate that BEE effectively improves spectrum utilization across various factors and offers operators effective guidance for price adjustments, thereby meeting the personalized spectrum management needs of 6G networks.**

***Index Terms*—Spectrum sharing, 6G networks, blockchain, evolutionary algorithm, evolutionary game theory.**

I. Introduction

RESEARCH on 6G networks has commenced alongside the full commercialization of diverse services and personalized applications on 5G networks. This next generation envisions a hyper-connected world with unprecedented performance and ubiquitous intelligence, driven by Space-Air-Ground Integrated Networks (SAGIN), Artificial Intelligence (AI), and demanding, disruptive applications, including holographic communication, integrated sensing and communication (ISAC), extended reality (XR), and digital twins [1]. 6G networks will introduce dynamic service provisioning within a service-driven network management framework to meet user preferences regarding speed, intelligence, privacy, cost, and energy consumption [2]. Consequently, to support these diverse and dynamic user-centric services, resource sharing among operators, encompassing computation, communication, storage, and data, is paramount in 6G [3]. In particular, spectrum sharing is fundamental, supporting task offloading via wireless communication and transmitting signaling messages in energy sharing [4]. While spectrum sharing research existed in previous generations, the unique characteristics of 6G, including an expanded spectrum range, heterogeneous vertical/horizontal massive ultra-dense networks, and diverse, dynamic service requirements, make dynamic spectrum sharing (DSS) more critical and challenging [5].

To support unprecedented performance metrics, 6G networks is envisioned as a full-spectrum communication system, spanning from sub-6 GHz to Terahertz (THz), including visible light communication (VLC) bands [6], as shown in Fig. 1. This extensive spectrum is divided into distinct bands, each categorized by its unique propagation characteristics and service capabilities. Low Band (<1 GHz) delivers broad area coverage and robust penetration for wide-area services and foundational communication. Mid Band (1–24 GHz) provides a balance between bandwidth and coverage for various types of pervasive services. High Band (24–300 GHz) enables high data rates and low latency for advanced services. THz Band (0.1–10 THz) promises vast bandwidths and extreme data rates for future ultra high-speed services [7]. VLC Band (400–800 THz) offers unlicensed, high bandwidth for specific services such as indoor positioning and SAGIN [8]. As demand for new services increases, the pressure on lower and mid bands intensifies, while the introduction of new frequency bands enhances 6G capabilities. Therefore, efficient and fine-grained allocation of existing frequency bands is as crucial as exploring new frequency bands for 6G [9].

However, realizing efficient DSS in 6G faces three significant challenges. Firstly, the full-spectrum communication of 6G leads to a highly fragmented spectrum landscape [10], which, combined with the diverse and dynamic service requirements of 6G, results in highly variable spectrum demand across volume, time, and space, necessitating more rapid and flexible DSS to accommodate instantaneous changes in network needs. Secondly, the heterogeneity and complexity of

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Kun Yan, Wenping Ma, and Weiwei Wang are with the School of Telecommunications Engineering, Xidian University, Xi'an 710071, China, and also with the State Key Laboratory of Intelligent Vehicle Safety Technology, Changan Automobile Co., Ltd, Chongqing 400044, China (e-mail: kyan@stu.xidian.edu.cn; wp_ma@mail.xidian.edu.cn; wweiwei@stu.xidian.edu.cn).

Shaohui Sun is with the State Key Laboratory of Wireless Mobile Communication, Datang Mobile Communications Equipment Co., Ltd, Beijing 100083, China (e-mail: sunshaohui@catt.cn).

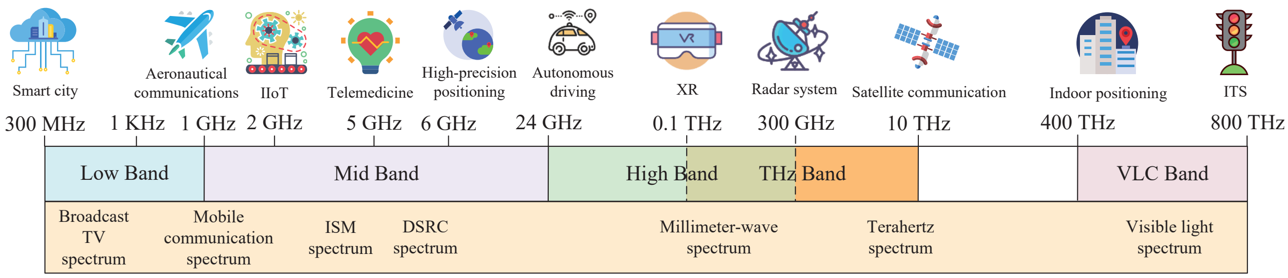

Fig. 1. Overview of the spectrum resources in 6G networks.

6G spectrum resources, further exacerbated by ISAC across diverse frequency bands, require sophisticated management strategies. Orchestrating these vastly different spectral characteristics and exploiting synergistic opportunities across diverse frequency ranges is necessary [11]. Thirdly, ultra-dense network deployments, particularly in higher frequency bands, with potentially thousands of small and ultra-small cells, pose challenges for interference management and resource coordination [12]. These technical complexities render traditional approaches increasingly inadequate, necessitating innovative, distributed, and intelligent solutions.

Despite the recognized potential of DSS to improve spectrum utilization, its practical implementation is significantly impeded by regulatory concerns regarding loss of control, substantial fees for exclusive usage rights, and legal prohibitions against inter-operator sharing [13], [14]. Existing DSS schemes, including auction-based and allocation-based approaches, grapple with limitations in fairness, efficiency, and adaptability to dynamic spectrum demands. Auction-based schemes can lead to monopolization, while allocation-based schemes struggle with resource reclamation [15], [16]. Furthermore, existing research predominantly concentrates on DSS among operators, overlooking the critical spectrum sharing requirements between operators and users. The scale and complexity of 6G networks are rendering traditional, centralized management inadequate. As 6G networks evolve towards more distributed, service-centric architectures, innovative solutions are needed to overcome these limitations by considering the multi-dimensional characteristics of 6G spectrum and the multifaceted nature of 6G services.

To address the unique challenges of DSS in 6G, this article proposes BEE, a distributed DSS mechanism for service-centric 6G networks. BEE leverages a sharding **B**lockchain to create a secure and distributed platform for spectrum management and trading, and employs **E**volutionary algorithms and **E**volutionary game theory to optimize spectrum allocation and utilization. BEE aims to implement a full-flow process from spectrum providers to user equipment (UEs). To the best of our knowledge, BEE is the first framework to utilize the improved Non-dominated Sorting Genetic Algorithm III (NSGA-III) for DSS. Specifically, the main contributions of this article are summarized as follows:

- We propose a secure, two-stage DSS mechanism for complex and ultra-dense service-centric 6G networks, leveraging sharding blockchain. It aims to provide distributed spectrum trading and fine-grained spectrum management.
- We propose a Proof of Spectrum (PoSP) mechanism for inter-shard consensus, adapting to the transaction environment of DSS. It is designed to ensure the requirements of massive scale and real-time services in 6G while maintaining the fairness of transactions.
- We utilize a tanh function-based NSGA-III (TNSGA-III) to implement a more comprehensive and intelligent spectrum allocation strategy. It employs multi-objective optimization (MOOP) to address the full-spectrum characteristics and dynamic service requirements of 6G.
- We leverage evolutionary game theory to assist operators in establishing, and users in choosing, service level agreements (SLAs) within more appropriate frequency bands. It aims to better address the diverse service and business demands of 6G.

The remainder of this article is structured as follows. We review related work in Section II. In Section III, we introduce the system framework of the proposed BEE and the working principles of sharding blockchain. In Section IV, we detail the spectrum allocation mechanism based on an evolutionary algorithm. In Section V, we present the spectrum trading scheme based on evolutionary game theory. In Section VI, we analyze the security and privacy protection of the proposed scheme. We present the simulation results in Section VII. Finally, we conclude this article in Section VIII.

II. Related Works

In this section, we present the view of service-centric 6G networks, discuss the study of spectrum management, and review blockchain-based DSS.

A. View of Service-Centric 6G Networks

Building upon the foundational performance of 4G, 5G networks has invested in additional spectrum and hardware resources, implementing a gradual evolutionary strategy to achieve a ubiquitous Internet of Things (IoT) [17]. Facilitated by AI, 6G networks will evolve based on the intent and usage patterns of new services and business requirements. Moreover, 6G networks will introduce dynamic service provisioning within a service-driven network management framework, empowering users to autonomously adjust their preferences regarding speed, intelligence, privacy, cost, and energy consumption [2]. Within this context, the security requirements for network verifiability and trustworthiness are driving the transformation of traditional network operators in 6G networks toward becoming virtual network service operators [18]. This suggests that future 6G networks will comprise numerous micro-mobile network operators, capable of supporting complex and diverse service requirements through flexible business models [9]. Blockchain will be employed to enhance the distributed and virtualized 6G network infrastructure, thereby simplifying service management among spectrum regulators, operators, and users. This transformation aims to accommodate the diverse needs of communications and networks across various IoT scenarios [19].

Current research primarily focuses on exploring diverse application scenarios for 6G networks under assumed communication and network conditions. While there are entirely new applications and disruptive upgrades to existing ones, it is undeniable that these advancements will be rooted in a human-centered, service-centric network [1]. Hence, sharing communication and networking resources among multiple virtual network operators, based on service requirements, characteristics, and levels, utilizing wireless virtualization technology, will form the cornerstone of establishing service-centric 6G networks [20].

B. Study of Spectrum Management

In radio resource management, the issue of spectrum allocation and sharing has been proven to be an NP-hard problem. Traditional schemes often utilize convex optimization to solve this problem [15]. However, this approach is relatively inefficient due to the significant computational resources and time required. Moreover, it struggles with the dynamics and uncertainties of spectrum resources, rendering it unsuitable for future network scenarios. Consequently, Chen *et al.* [16] proposed the EDA and MDA algorithms. Both of these algorithms can achieve interference-free matching with guaranteed minimum spectrum requirements. Chen *et al.* [21] proposed a spectrum allocation scheme based on Lagrangian duality and the Kuhn-Munkres algorithm to obtain optimal power and channel allocation, respectively. Su *et al.* [22] proposed a Q-learning-based spectrum access scheme for content delivery. Marwani *et al.* [23] proposed a spectrum allocation solution based on graph neural networks for non-orthogonal wireless environments. While these approaches frequently yield optimal solutions, the future evolution of 6G networks will prioritize security and privacy. This shift may present challenges for spectrum management and sharing, necessitating decision-making based on multiple factors.

Given the dynamic and uncertain characteristics of spectrum allocation, evolutionary algorithm-based schemes are attracting increasing attention [24]. This is because evolutionary algorithms provide a robust approach for addressing such complex optimization problems. Inspired by natural selection and genetic principles, they iteratively evolve a population of candidate solutions toward an optimal set using operators such as selection, crossover, and mutation. They are particularly effective in exploring large and complex search spaces to identify high-quality solutions where traditional optimization methods may fall short. This method maps spectrum allocation to a MOOP, allowing for flexible configuration of subband attributes. It can adaptively and dynamically adjust the population evolution direction to search for the optimal solution. Moreover, its insensitivity to initial data ensures user privacy [25]. Furthermore, compared to Q-learning-based approaches, resource allocation schemes utilizing evolutionary algorithms can achieve better Quality of Service and Quality of Experience by optimizing network resources through continuous iteration [26]. Additionally, most studies have focused solely on DSS among operators, neglecting the DSS demands between operators and users.

C. Study of Blockchain-Based DSS

Driven by the stringent latency requirements and the demand for higher scalability in 6G, wireless communication networks are exploring distributed or multi-center management architectures [27]. This trend positions blockchain as a particularly suitable technology. Blockchain is a decentralized and cryptographically secured digital ledger that records transactions in a verifiable and immutable manner across a distributed network of nodes. It eliminates the need for a central intermediary, fostering trust, transparency, and accountability among participants. Its inherent characteristics, particularly decentralization, can facilitate trust and transparency among multiple stakeholders in 6G network management [28]. Furthermore, these attributes make blockchain particularly well-suited for complex coordination tasks such as DSS, in which secure and auditable tracking of spectrum rights, allocations, and usage is critical.

Consequently, by leveraging the security and openness of blockchain, 6G distributed spectrum resource management and transactions can be fortified, mitigating information asymmetry among parties involved in spectrum sharing [29]. Zhang *et al.* [30] proposed a user-autonomous spectrum sharing model for large-scale IoT in 6G networks, which leverages blockchain to minimize single points of failure. Li *et al.* [31] proposed a spectrum sharing framework based on consortium blockchain, which employs smart contracts to enhance the security and efficiency of DSS. Wang *et al.* [32] proposed a dynamic, demand-driven spectrum sharing model for UAV networks, in which blockchain is utilized to ensure fairness and reliability in spectrum transactions. Sun *et al.* [33] proposed an energy-efficient spectrum sharing framework for 6G UIoT networks, which leverages a hybrid blockchain integrated with 6G cloud services. Although the above DSS schemes focus on utilizing blockchain to achieve secure and reliable distributed scenarios, the practical applicability of blockchain is often overlooked. For example, a blockchain utilizing DAG can reduce the Proof of Work (PoW) burden on the system [4], [30], but may compromise the consistency of the model [34]. Therefore, developing applicable blockchain and consensus mechanisms specifically for DSS in 6G networks is necessary.

An overview of related works is given in Table I. Distinct from the aforementioned works, BEE is designed for pre-divided frequency bands supporting service-centric IoT in 6G networks. It employs a sharding blockchain as the foundational framework to achieve fine-grained DSS across many objectives, aided by TNSGA-III and evolutionary game theory.

TABLE I
DIFFERENCES BETWEEN BEE AND OTHER MAIN RELATED WORKS

Ref.	Core Scenario	Spectrum Sharing Mechanism	Blockchain Features	Price-oriented	Service-centric	Security and Privacy	6G Relevance
[16]	Spectrum allocation market with minimum/maximum quotas	Matching Theory (EDA, MDA)	×	×	×	×	×
[21]	Energy-efficient and secure D2D communications underlaying UAV-enabled networks	Alternating Optimization, Lagrangian Dual, Kuhn-Munkres	×	×	×	✓	×
[22]	Spectrum access for content delivery in mobile networks	Q-Learning, Stackelberg Game	×	✓	✓	×	×
[23]	Spectrum Allocation in N-link Interference Channels	Graph Neural Networks	×	×	×	×	✓
[30]	User-autonomy spectrum sharing for 6G-enabled IoT	Swarm Intelligence	✓(DAG Blockchain)	×	✓	✓	✓
[31]	Multi-operator MNO DSS	MLMF Stackelberg Game	✓(Consortium Blockchain)	✓	×	✓	✓
[32]	Multi-operator spectrum sharing in UAV communication systems	Combinatorial Auctions, Stackelberg Games	✓(Consortium Blockchain)	✓	×	✓	×
[33]	Energy-Efficient Spectrum Sharing for 6G UIoT Networks	Reinforcement Learning	✓(Hybrid Blockchain)	×	×	✓	✓
BEE	Full-flow DSS for Service-Centric 6G Networks	TNSGA-III (MOOP), Evolutionary Game Theory	✓(Sharding Blockchain)	✓	✓	✓	✓

III. BEE: A SHARDING BLOCKCHAIN-BASED DSS MECHANISM

In this section, we first present the composition and structure of BEE, followed by a detailed explanation of its workflow utilizing sharding blockchain.

A. Overview of BEE

The proposed BEE scheme primarily leverages sharding blockchain, evolutionary algorithm, and evolutionary game theory to achieve DSS, spanning from spectrum allocation to user equipment access. The proposed mechanism consists of five main members:

- Spectrum Regulator (SR): The SR is typically the government agency with the highest level of control over spectrum resources.
- Primary Mobile Network Operators (PMNOs): PMNOs can directly utilize key frequency bands allocated by SR, thereby facilitating the provision of comprehensive communication resources for 6G networks to fulfill the requirements of pervasive network services.
- Virtual Service Network Operators (VSNOs): VSNOs procure spectrum resources from PMNOs and then strategically optimize them for specific scenarios, prioritizing efforts to ensure their own advantages in each service, thereby achieving diversified, service-centric 6G networks.
- User Equipment (UEs): UEs can access the pervasive network services provided by PMNOs or the specifically optimized network services provided by VSNOs using their blockchain identity (blockchain wallet address).
- Edge Computing Service Providers (ECSPs): ECSPs play a crucial role as one of the primary infrastructure components in 6G networks facilitating AI-based services. Furthermore, in BEE, ECSPs are established as vital internal components of both PMNOs and VSNOs, responsible for executing evolutionary algorithms and maintaining the sharding blockchain.

We consider a multi-service 6G networks, where each PMNO and VSNO in the physical network possesses its own base stations. UEs access nearby base stations to obtain specific services. The BEE divides the network into multiple service committees based on service type. Furthermore, spectrum allocation between PMNOs and VSNOs is managed by an allocation committee, as shown in Fig. 2. The workflow unfolds in two primary stages, underpinned by a sharding blockchain that ensures transparent and secure record-keeping of all transactions and state changes. In the first stage, PMNOs announce their available frequency bands after satisfying their internal spectrum demands. The allocation committee then facilitates the spectrum trading process. Specifically, when VSNOs submit their spectrum requests, the TNSGA-III algorithm is invoked to determine an optimal allocation strategy that balances multiple objectives. The resulting trade agreement is recorded on the blockchain, thus completing the initial phase of BEE. In the second stage, after acquiring spectrum, VSNOs customize the spectrum use for their specific services. Within their designated service committees, VSNOs engage in dynamic spectrum trading with UEs. This interaction is modeled and optimized using evolutionary game theory, enabling adaptive pricing and efficient resource utilization strategies. These decisions are subsequently recorded and managed on the blockchain, thereby establishing a comprehensive and auditable DSS framework.

Compared to traditional blockchain-based approaches, a

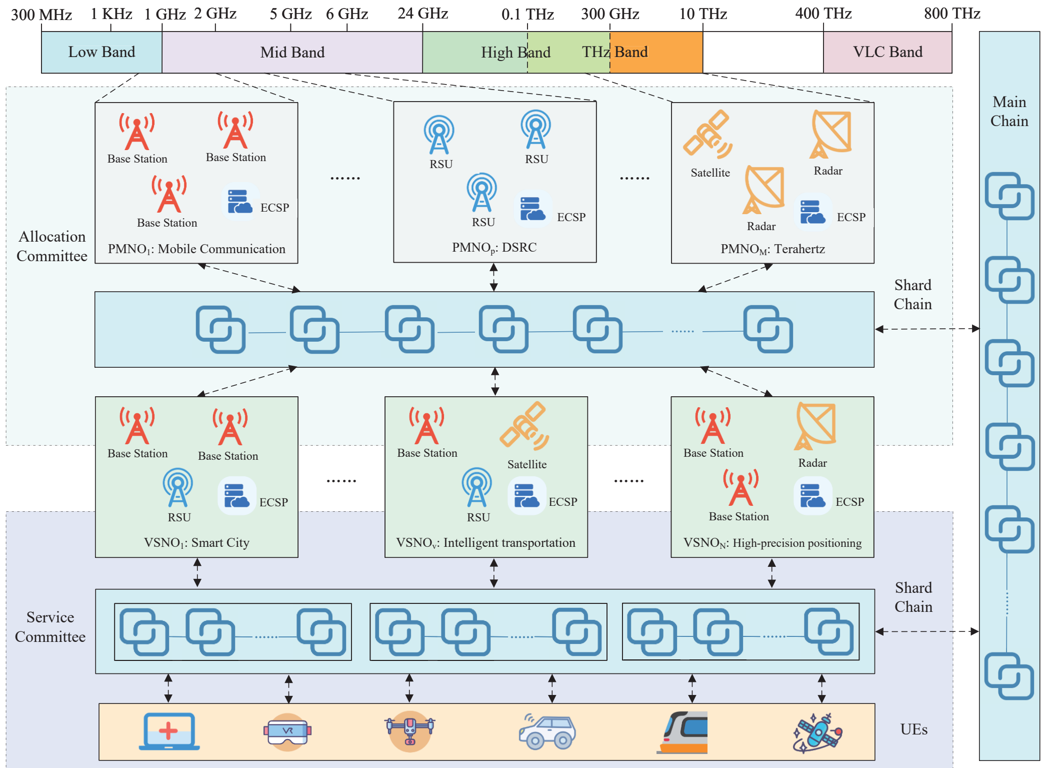

Fig. 2. System model of BEE.

sharding blockchain divides the entire system into multiple independent shards. Each shard processes and stores only a subset of the overall data and transactions in parallel, significantly improving throughput and scalability [35]. To maintain consistency and security across these independent shards, a sharding blockchain necessitates two distinct consensus mechanisms: intra-shard consensus, focused on efficiently validating transactions within a shard, and inter-shard consensus, focused on ensuring global consistency and security by managing cross-shard communication and state synchronization.

In BEE, intra-shard consensus is achieved within the service and allocation committees, which utilize shard chains to package transaction information. In contrast, the main chain is responsible for collecting, broadcasting, and synchronizing consensus information from the shard chains to achieve inter-shard consensus. Specifically, members within each committee primarily focus on transactions directly relevant to them. Therefore, these transactions are packaged and broadcast exclusively within their respective committees, achieving rapid intra-shard consensus. Simultaneously, the inter-shard consensus mechanism is responsible for the management of spectrum resource state updates and the global synchronization of intra-shard consensus results.

B. Initialization of BEE

To ensure the security of spectrum resources and the unforgeability of spectrum transactions, PMNOs, VSNOs, and UEs must undergo authentication with their real identity information by SR upon entering the BEE. Subsequently, they are each assigned a unique blockchain wallet. Each blockchain wallet contains the holder's public key, private key, wallet address, and account balance. Additionally, PMNOs' wallets contain tradable spectrum, VSNOs' wallets contain service types, and UEs' wallets contain identifiers for the required services. PMNOs and VSNOs can communicate and trade spectrum through wallet addresses, while UEs can utilize wallet address to access the bands provided by PMNOs or VSNOs for their required services. Simultaneously, the SR can trace and audit transactions within the system using wallet addresses to ensure the security of transactions.

In general, spectrum resources in a country or region are typically allocated to a few major network operators (e.g., T-Mobile, AT&T, China Mobile, etc.) due to their continuous construction, maintenance, and control of communication network infrastructure. In BEE, PMNOs obtain the primary right to use and allocate spectrum resources from the SR. They divide the acquired spectrum resources using wireless virtualization technology [36], reserve frequency bands necessary to support their services, and simultaneously sublet free bands to VSNOs. This is achieved through smart contracts deployed on the sharding blockchain to enhance the spectrum utilization. Additionally, the revenue obtained from VSNOs can offset the expenses associated with constructing communication network infrastructure.

C. Intra-Shard Consensus

There are two main types of intra-shard transactions: those between PMNOs and VSNOs, and those between VSNOs and UEs. In the sharding blockchain of BEE, Practical Byzantine Fault Tolerance (PBFT) is employed to achieve consensus within both the service committee and the allocation committee for transactions related to spectrum allocation and sharing. PBFT is particularly appropriate for this task because it can achieve consensus quickly and efficiently within relatively small groups of nodes [37]. The following transactions are considered in the PBFT-based intra-shard consensus:

1) Transactions between PMNOs and VSNOs: As a spectrum provider, the m-th PMNO, after acquiring and dividing spectrum resources, broadcasts the information (encapsulated as Sel_m) about the sublet of its free bands to the allocation committee. More precisely, Sel_m is defined as follows:

$$Sel_m = \{Wid_m, Ban_m, Sfe_m, Loc_m, Tim_m\}, \quad (1)$$

where Wid_m represents the blockchain wallet address of the m-th PMNO, and Ban_m, Sfe_m, Loc_m, and Tim_m represent the spectrum information, anticipated selling price, location, and time of the bands to be sold, respectively.

As a spectrum requester, the n-th VSNO, after specifying its desired frequency bands, utilizes TNSGA-III to seek the most appropriate PMNO from which to acquire spectrum resources. It then sends a purchase request (encapsulated as Req) to the PMNO. More precisely, Req_n is defined as follows:

$$Req_n = \{Wid_n, Ban_n, Bfe_n, Loc_n, Tim_n\}, \quad (2)$$

where Bfe_n is the anticipated purchase price of the bands to be bought.

2) Transactions between VSNOs and UEs: After acquiring the required spectrum resources, VSNOs optimize them in accordance with the services they offer. SLAs are then formulated based on the outcomes of cost analysis and evolutionary game theory and are broadcast within the service committees. Considering the possibility of multiple VSNOs offering the same service, UEs have the option to select from a variety of SLAs provided by different VSNOs. After choosing their preferred SLA, UEs access the relevant VSNO's network through a smart contract.

Subsequently, an agreement on the spectrum resources transaction can be reached through smart contracts. Utilizing PBFT, this transaction will be packaged into a new block within the shard chain and then broadcasted to the committee, ensuring a consistent view of the local ledger among all nodes within the shard.

D. Inter-Shard Consensus

To guarantee global consensus and manage spectrum resource state updates across BEE, inter-shard consensus is implemented. ECSPs function as the crucial bridge, maintaining the main chain, which periodically synchronizes consensus information from each shard chain. PoSP is designed to implement inter-shard consensus, ensuring transaction fairness and security. PoSP is based on the currently most mainstream and proven secure consensus mechanism, PoW, which can support large-scale commercialization [38], while innovatively incorporating the spectrum situation of VSNOs to dynamically adjust mining difficulty. In this context, the mining difficulty is not constant but varies among participants. It has the form as follows:

$$\begin{aligned} &\text{Find } n \\ &\text{s.t.} \quad \text{SHA256}(\text{SHA256}(b.n)) < target * \tau * S * \mathcal{N}, \end{aligned} \quad (3)$$

with

$$S = \alpha_1 ban + \alpha_2 tim + \alpha_3 num, \quad (4)$$

where "." is a string concatenation operator, b is the newest block, n is the nonce, $target$ represents the mining difficulty, which is the same as in PoW. τ represents the time since an ECSP last successfully packaged a block, $\mathcal{N}$ is a random number generated through the verifiable random function (VRF), S denotes the spectrum situation held by VSNOs, including bandwidth ban, time tim, and the number of UEs served num, α_1, α_2, α_3 are weight factors, and $\alpha_1 + \alpha_2 + \alpha_3 = 1$.

In contrast to traditional PoW, PoSP mitigates the impact of computational competition on the system by adjusting the mining difficulty for participants. Specifically, the larger the value of S, the more reliable the VSNOs are considered, and the higher the probability of obtaining the bookkeeping right. Meanwhile, to prevent VSNOs with more spectrum resources from monopolizing the bookkeeping right and engaging in malicious behaviors, the value of τ for a bookkeeper who successfully packages a block will be reset to 1. This makes it almost impossible for them to obtain the bookkeeping right within a certain period. Furthermore, to further enhance the fairness of bookkeeping competition, $\mathcal{N}$, based on VRF, is utilized. To prevent $\mathcal{N}$ from exerting too much influence on the bookkeeping result and to avoid potential collusive attacks by VSNOs with a lower S, we choose a value for N that is an order of magnitude smaller than S. Due to the randomness of $\mathcal{N}$, the attribution of bookkeeping rights becomes more unpredictable, while the validation of $\mathcal{N}$ ensures that the results of bookkeeping competition are reasonable and auditable.

IV. Spectrum Allocation Based on TNSGA-III

In this section, we utilize the first stage of BEE: an allocation-based scheme to address DSS between PMNOs and VSNOs. We model it as a MOOP with four conflicting objectives and utilize a TNSGA-III for the analysis.

A. Network Model

We consider the uplink of a 6G networks based on Orthogonal Frequency Division Multiplexing. Let $P = \{P_1, \cdots, P_m, \cdots, P_M\}$ represent the set of all PMNOs, and $V = \{V_1, \cdots, V_n, \cdots, V_N\}$ represent the set of all VSNOs. Assuming that the spectrum resources are divided into K discrete subbands, each with a bandwidth of B Hz. PMNOs retain the subbands they require, and the free subbands will be sublet and shared with VSNOs. UEs can access services provided by either PMNOs or VSNOs, depending on their specific requirements.

B. Objective Functions

Minimizing interference to participants resulting from spectrum reuse is a critical consideration in spectrum sharing. Such interference can introduce additional noise, resulting in a decrease in the Signal-to-Interference-plus-Noise Ratio (SINR) and a consequent reduction in spectrum utilization. The received SINR at the m-th PMNO receiver and the n-th VSNO receiver on the k-th subband can be calculated as follows:

$$SINR_{m,P}^{k} = \frac{p_m^k g_{m,B}^k}{\sigma^2 + \sum_{n=1}^{N} p_n^k g_{n,B}^k}, \tag{5}$$

and

$$SINR_{n,V}^{k} = \frac{p_n^k g_{n,B}^k}{\sigma^2 + \sum_{m=1}^{M} p_m^k g_{m,n}^k + \sum_{n=1}^{N} p_n^k g_{n,n'}^k}, \tag{6}$$

where p_m^k, p_n^k, $g_{m,B}^k$, $g_{n,B}^k$ represent the transmit power of the receiver of the m-th PMNO and the n-th VSNO, and the channel power gain between the receiver and the base station in k-th subband, respectively, $g_{m,n}^k$ is the channel power gain between the receiver of the m-th PMNO and the n-th VSNO in k-th subband, and $g_{n,n'}^k$ is the channel power gain between the receiver of the n-th VSNO and the n'-th VSNO in k-th subband, σ^2 denotes the noise power.

According to the Shannon-Hartley theorem, the achievable data rate of the m-th PMNO receiver and the n-th VSNO receiver at the k-th subband can be represented as follows:

$$R_{m,P}^{k} = B \log_2 \left(1 + SINR_{m,P}^{k}\right), \tag{7}$$

and

$$R_{n,V}^{k} = B \log_2 \left(1 + SINR_{n,V}^{k}\right). \tag{8}$$

Therefore, we establish the following factors for evaluating the spectrum utilization.

1) Subbands occupancy: As a direct factor influencing spectrum utilization, it can be quantified as the number of all VSNOs participating in DSS while ensuring the provision of all network services. It is defined as follows:

$$f_1(x) = \sum_{n=1}^{N} x_n, \tag{9}$$

with

$$x_n = \begin{cases} 1 & SINR_{m,P}^{k} \geq SINR_{0,P}^{k}, SINR_{n,V}^{k} \geq SINR_{0,V}^{k} \\ 0 & \text{otherwise} \end{cases}, \tag{10}$$

where $SINR_{0,P}^{k}$ and $SINR_{0,V}^{k}$ are the thresholds of SINR on the k-th subband for PMNOs and VSNOs, respectively.

2) Throughput: This factor signifies the aggregate throughput from both PMNOs and VSNOs within the current network, serving as an indicator of the overall network performance. It can be represented as follows:

$$f_2(x) = \sum_{m=1}^{M} R_{m,P}^{k} + \sum_{n=1}^{N} R_{n,V}^{k} x_n. \tag{11}$$

3) Transmit power: Energy efficiency is also a crucial aspect in the design of green 6G networks [1]. Consequently, the total transmit power from both PMNOs and VSNOs is utilized to evaluate the current energy consumption in the network. It can be calculated as follows:

$$f_3(x) = \sum_{m=1}^{M} p_m^k + \sum_{n=1}^{N} p_n^k x_n. \tag{12}$$

4) Revenue: This is the most effective method for encouraging active participation of PMNOs in spectrum sharing. The logarithmic utility function is used to quantify the revenue that PMNOs gain from VSNOs through spectrum sharing. It is defined as follows:

$$f_4(x) = \sum_{n=1}^{N} \ln\left(1 + \beta_1 R_{n,V}^{k} + \beta_2 T_n^k\right) x_n, \tag{13}$$

where T_n^k represents the time that VSNOs sublet the k-th subband from PMNOs, β_1, β_2 are weight factors, and $\beta_1 + \beta_2 = 1$.

C. MOOP Formulation and Constraints

Reasonably allocating free subbands from PMNOs to VSNOs can enhance the spectrum utilization of the entire network. However, focusing exclusively on subbands occupancy while neglecting other factors is futile. Therefore, it is crucial to examine the trade-offs among these conflicting objectives. In BEE, our goal is to simultaneously maximize throughput and subband occupancy, ensure revenue for PMNOs through spectrum sharing, and minimize transmit power. The MOOP is formulated as:

$$\max\left\{f_1(x), f_2(x), f_4(x)\right\}, \tag{14}$$

$$\min\left\{f_3(x)\right\}, \tag{15}$$

subject to:

$$f_1(x) \leq K, \tag{16}$$

$$SINR_{m,P}^{k} \geq SINR_{0,P}^{k}, \forall m \in 1,...,M, k \in 1,...,K, \tag{17}$$

$$SINR_{n,V}^{k} \geq SINR_{0,V}^{k}, \forall n \in 1,...,N, k \in 1,...,K, \tag{18}$$

$$p_m^k \leq p_{\max}^k, \forall m \in 1,...,M, k \in 1,...,K, \tag{19}$$

$$p_n^k \leq p_{\max}^k, \forall n \in 1,...,N, k \in 1,...,K, \tag{20}$$

where $p_{\max}^k$ denote the maximum transmit power.

Constraint (16) specifies that the number of subbands occupied by VSNOs should not surpass the total number of subbands. Constraints (17) and (18) define the SINR threshold requirements for the transmission of both PMNOs and VSNOs. Constraints (19) and (20) restrict the maximum transmit power available to all PMNOs and VSNOs in the network, ensuring compliance with green 6G networks requirements.

D. Spectrum Allocation Using TNSGA-III

As an evolutionary algorithm, NSGA-III can utilize multiple candidate solutions during the population evolution process to ensure population diversity, thereby avoiding convergence to a local optimum when solving MOOP [39]. Simultaneously, NSGA-III tackles high-dimensional problems by maintaining population diversity through uniformly distributed reference points. This makes it significantly more effective than NSGA-II in achieving multi-objective convergence, especially for problems with more than three objectives [40]. We utilize TNSGA-III to balance the aforementioned four objectives, and the detailed procedure is as follows:

Step 1 (Encoding for Allocation Strategies:) As shown in Fig. 3, a chromosome, composed of multiple genes, is utilized to represent a spectrum allocation strategy. Each gene in the chromosome corresponds directly to a subband, thereby ensuring that the number of genes aligns with the number of subbands. The chromosome remains unique throughout each iteration [41]. The occupancy status of all subbands determines the gene encoding, establishing a mapping between the gene encoding and subband status. This mapping allows PMNOs to dynamically update their lists of available subbands.

Without loss of generality, the i-th chromosome in the j-th iteration is encoded as

$$C_i^j = \{g_1, \cdots, g_k, \cdots, g_K\}, \tag{21}$$

with

$$g_k = \begin{cases} 0 & k\text{-th subband is free} \\ 1 & k\text{-th subband is occupied by PMNOs} \\ 2 & k\text{-th subband is occupied by VSNOs} \end{cases}. \tag{22}$$

Fig. 3 visualizes the chromosome and gene encoding. The first subband is occupied by PMNOs, VSNOs occupy the third and k-th subbands, while the second and K-th subbands are free.

Step 2 (Fitness Function and Constraints:) The fitness function is utilized to evaluate the viability of chromosomes during the evolutionary process. Generally, chromosomes with lower fitness can survive the subsequent iteration of the goal minimization problem [41], representing a superior spectrum allocation strategy in BEE.

BEE aims to maximize subbands occupancy, throughput, and revenue while minimizing transmit power to achieve efficient and energy-efficient DSS in 6G networks. If the chromosome does not satisfy the constraints (16)-(20), it indicates that the chromosome fails to meet the viability criterion and will be eliminated during the evolutionary process. In summary, the fitness vector for the MOOP of BEE can be represented as:

$$F(C_i^j) = [f_1(C_i^j), f_2(C_i^j), f_3(C_i^j), f_4(C_i^j)] \tag{23}$$

Step 3 (Crossover and Mutation Operation:) In the NSGA-III, the generation of offspring involves crossover and mutation operations on parent chromosomes. Two chromosomes exchange genetic material by swapping genes around the crossover point, creating new chromosomes, and thus forming new spectrum allocation strategies. Mutation operations aim to create chromosomes with potentially higher fitness by modifying individual genes, thus directly influencing the rate and quality of evolution. Typically, a small mutation rate can lead to genetic drift, whereas a large mutation rate can lead to the loss of good solutions. In other words, at the start of the evolution, a large mutation rate enhances population diversity, facilitating the discovery of good solutions. Conversely, at the end of the evolution, a small mutation rate facilitates retaining good solutions. However, NSGA-III uses a fixed mutation rate, which in practice often restricts the evolutionary search, produces undesirable offspring, and wastes computational resources. Therefore, TNSGA-III associates the mutation rate with the number of evolutionary iterations and utilizes the tanh function to dynamically and adaptively adjust the mutation rate. The mutation rate can be calculated as follows:

$$mr = \frac{e + e^{-1}}{e - e^{-1}} \tanh\left(\frac{TI - CI}{TI}\right), \tag{24}$$

where CI and TI represent the current and maximum number of evolutionary iterations, respectively.

Step 4 (Population Evolution:) After the crossover and mutation operations, new chromosomes are generated. The initialized population undergoes iterations, as shown in Algorithm 1, to generate the final population, X^{TI}, which contains the optimal spectrum allocation strategy.

Algorithm 1 Population Evolution

Input: The initialized population X^0, the total iterations TI, and the population size PN

Output: the final population X^{TI}

for $j = 1$ to TI **do**
  for $C_i^j \in X^{j-1}$ **do**
    Calculate $F(C_i^j)$ according to (23);
  end for
  Calculate the mutation rate according to (24);
  Crossover and mutation operations, generate a merged population of $2PN$;
  for merged population **do**
    Non-dominated sort;
  end for
  Determine the reference point on the hyper-plane;
  Associate chromosomes and reference points;
  Niche-preservation Operation, generate a new population X^j;
end for
return X^{TI}

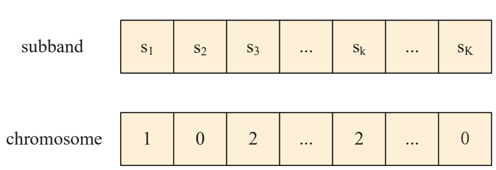

Fig. 3. Encoding of subband.

E. Optimum Selection

After numerous iterations, the final population comprises a set of optimal feasible solutions for spectrum allocation, generally known as Pareto solutions. A deterministic proposal is needed, and therefore Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method is employed to evaluate the most perfect solution among many Pareto solutions. As an evaluation method for approximating the ideal solution, TOPSIS can rapidly identify the optimal solution by ranking the distance between all solutions and the positive (negative) ideal solution. Simultaneously, the entropy weight method can effectively eliminate the arbitrariness associated with subjectively determining the weight of indicators. The combination of the two methods can objectively and impartially provide the optimal spectrum purchase proposal. The specific algorithm is detailed in [42].

As all spectrum transactions take place on the sharding blockchain, the allocation and occupancy status of subbands are promptly synchronized among all PMNOs and VSNOs. This implies that the initial population can be generated either randomly or by using information about the current subband occupancy in the network, enhancing the reasonableness of the final solution.

In BEE, PMNOs can set the selling price and time more rationally by analyzing the optimal solution from the final population for their respective free subbands. Similarly, VSNOs can determine their offer prices by analyzing the optimal solution of the final population for the subbands they plan to sublet. Thus, PMNOs and VSNOs can share and trade spectrum flexibly, dynamically, and securely. Additionally, other factors, such as delay, risk, and region, can be considered as factors in MOOP. The optimal solution can be sought using TNSGA-III for fine-grained DSS.

V. Spectrum Trading Based on Evolutionary Game Theory

In this section, we introduce the second stage of BEE, which applies evolutionary game theory to address spectrum trading between VSNOs and UEs.

A. Problem Descriptions and Assumptions

VSNOs optimize their acquired spectrum resources and establish various SLAs to attract UEs. UEs choose among different VSNOs and SLAs to meet their communications and networks requirements. VSNOs must balance SLAs and costs to maximize their payoffs while still attracting UEs. For UEs, different VSNOs and SLAs offer different rewards, prompting them to adjust their choices to maximize their own benefits. This dynamic forms the primary objective of spectrum trading between VSNOs and UEs [43].

In practical scenarios, the choices of VSNOs and SLAs made by UEs are influenced not only by their individual requirements but also by the choices of others. Furthermore, VSNOs dynamically adjust the pricing of SLAs in response to the selections of UEs. Evolutionary Game Theory provides a robust analytical framework for analyzing strategic interactions among agents (e.g., VSNOs and UEs). It models the adoption and propagation of strategies among agent populations based on their relative performance over time. It focuses on the dynamics of strategy selection, where agents iteratively learn or imitate rewarding behaviors, driving the system through an evolutionary process toward stable strategic equilibria. Consequently, an evolutionary game theory model can be developed for analyzing the UEs' choices. This model can continually offer adjustment suggestions for VSNOs' SLAs, thereby improving spectrum trading efficiency and enhancing spectrum utilization. The symbols and their descriptions for the proposed game model are shown in Table II.

TABLE II
Notations of the Evolutionary Game Theory Model

Symbol	Description
U_u	The u-th UEs in spectrum trading
I_u	The benefits U_u gains from utilizing the spectrum
D_u	The cost to U_u of purchasing SLAs
γ_u	The adjustment rate for the benefits of U_u, $\gamma_u \leq 1$
δ_u	The adjustment rate for the prices of n-th VSNO
RN_u	In general cases, the payoffs of U_u, $RN_u = I_u - D_u$
RE_u	In special cases, the payoffs of U_u, $RE_u = \gamma_u I_u - \delta_u D_u$
ΔR_u	The difference in payoff of U_u, $\Delta R_u = RE_u - RN_u$

The following assumptions and requirements apply throughout this section.

1) UEs have multiple VSNOs to choose from for the same network service.
2) The purchase in this section prefers to choose the n-th VSNO rather than choosing among the SLAs.
3) When network burdens are excessive in VSNOs, they are typically not solved by acquiring new subbands.

B. Game Model and Payoff Matrix

In this game, the model representing the selection of SLAs provided by n-th VSNO among UEs is denoted by a quaternion array $G = (P, N, S, U)$, where:

- P: All UEs in the system can participate in the game, assume UEs participating in this game are U_A and U_B;
- N: A collection of individual UEs;
- S: The UEs' strategy space $S = (s_1, s_2)$ =(purchase, not purchase) in this game, in which UEs are free to choose their strategies.
- U: The payoff matrix generated by UEs in the game, as shown in Table III.

TABLE III
Payoff Matrix for UEs

The strategy of U_A	The strategy of U_B	
	Purchase	Not Purchase
Purchase	$\gamma_A I_A - \delta_A D_A$, $\gamma_B I_B - \delta_B D_B$	$I_A - D_A$, 0
Not Purchase	0, $I_B - D_B$	0, 0

There are four strategy combinations generated by U_A and U_B in their selection of SLAs. As UEs in this game can only choose to purchase or not purchase, the game between U_A and U_B conforms to a general two-person symmetric game, and can be analyzed using standard methods [44]. U_u is utilized to denote the UEs involved in the game, aiming to enhance the clarity of the evolutionary game analysis.

In the strategy combination (purchase, purchase), the proliferation of UEs in the n-th VSNO inevitably leads to communications and networks burdens, resulting in a degradation

TABLE IV
EVOLUTIONARY STABLE STRATEGY ANALYSIS

State	Situation	Description	Evolution Strategy Analysis
1	$0 > D_u - I_u > G_u$	$RN_u > 0; RE_u < 0; \Delta R_u < 0$	$F'_u(x_1) > 0; F'_u(x_2) > 0; F'_u(x_3) < 0$
			EEP: x_3; ES: x_3 ratio of UEs choosing to purchase in evolution results
2	$D_u - I_u > 0 > G_u$	$RN_u < 0; RE_u < 0; \Delta R_u < 0$	$F'_u(x_1) < 0; F'_u(x_2) > 0; x_3 < 0$, does not exist
			EEP: x_1; ES: Not Purchase
3	$D_u - I_u > G_u > 0$	$RN_u < 0; RE_u < 0; \Delta R_u > 0$	$F'_u(x_1) < 0; F'_u(x_2) > 0; x_3 > 1$, does not exist
			EEP: x_1; ES: Not Purchase
4	$0 < D_u - I_u < G_u$	$RN_u < 0; RE_u > 0; \Delta R_u > 0$	$F'_u(x_1) < 0; F'_u(x_2) < 0; F'_u(x_3) > 0$
			EEP: x_3; ES: $x \in (0, x_3)$, Not Purchase, and $x \in (x_3, 1)$, Purchase
5	$D_u - I_u < 0 < G_u$	$RN_u > 0; RE_u > 0; \Delta R_u > 0$	$F'_u(x_1) > 0; F'_u(x_2) < 0; x_3 < 0$, does not exist
			EEP: x_2; ES: Purchase
6	$D_u - I_u < G_u < 0$	$RN_u > 0; RE_u > 0; \Delta R_u < 0$	$F'_u(x_1) > 0; F'_u(x_2) < 0; x_3 > 1$, does not exist
			EEP: x_2; ES: Purchase

of service quality. Therefore, the n-th VSNO needs to adjust the price of SLAs: either decreasing the price ($\delta_u < 1$) to compensate existing users or increasing the price ($\delta_u > 1$) to prevent new UEs from accessing the network. In other strategy combinations, when the network has sufficient resources, the n-th VSNO may need to adjust the price of its SLAs to attract UEs and enhance its profitability. In an optimal gaming environment, VSNOs and UEs will reach a mutually beneficial equilibrium.

C. Equilibrium Analysis

The UEs in this game belong to group N, and their probabilities of choosing to purchase and not to purchase are x and $1-x$, respectively. According to the payoff matrix in Table III. and the principles of evolutionary game theory, the expected payoffs for U_u choosing to purchase (s_1) or not purchase (s_2) can be obtained as follows:

$$\begin{aligned} E_u(s_1, x) &= x(\gamma_u I_u - \delta_u D_u) + (1-x)(I_u - D_u) \\ &= x(\gamma_u I_u - \delta_u D_u - I_u + D_u) + (I_u - D_u), \end{aligned} \tag{25}$$

and

$$E_u(s_2, x) = 0, \tag{26}$$

respectively.

Hence, the average expected benefit of U_u can be computed as

$$\begin{aligned} \bar{E}_u &= x E_u(s_1, x) \\ &= x^2(\gamma_u I_u - \delta_u D_u - I_u + D_u) + x(I_u - D_u). \end{aligned} \tag{27}$$

Then, the growth rate of the purchase strategy can be expressed by the dynamic equation for U_u's decision to purchase the SLAs of the n-th VSNO, as follows:

$$\begin{aligned} F_u(x) &= x\left(E_u(s_1, x) - \bar{E}_u\right) \\ &= x(1-x)\left[x\left(\gamma_u I_u - I_u + D_u - \delta_u D_u\right) + (I_u - D_u)\right], \end{aligned} \tag{28}$$

Let $F_u(x) = 0$, indicating that the growth rate of the purchase strategy reaches 0, leading the game toward a more stable state. This yields three evolutionarily stable strategies (ESS): $x_1 = 0$, $x_2 = 1$, and $x_3 = \frac{D_u - I_u}{\gamma_u I_u - I_u + D_u - \delta_u D_u}$, respectively.

D. Steady and Dynamic State Analysis

According to the theory of ESS, the steady state of a dynamic system should remain stable, even in the presence of small disturbances [45]. For brevity, if x is an evolutionary equilibrium point (EEP), it should satisfy the derivative $F'_u(x) < 0$. Therefore, the evolutionary strategies (ES) for UEs' purchasing decisions can be analyzed under different conditions based on the aforementioned three ESS candidates, as shown in Table IV, where $G_u = \gamma_u I_u - I_u + D_u - \delta_u D_u$.

This game exhibits four steady states (2, 3, 5, 6) and two dynamic states (1, 4). The evolutionary trend is influenced by several factors, including the payoffs and cost for U_u, the adjustment rate of the benefits and prices, and the initial ratio of UEs choosing to purchase. When all other parameters are fixed, the adjustment rate of prices can serve as a guide for the UEs' decisions.

In steady states 2 and 3, UEs consistently experience negative payoffs in both general and special cases. This prompts UEs to adopt the not purchase strategy. Specifically, in steady state 3, $\Delta R_u > 0$, indicating that the VSNOs' spectrum resources are heavily congested. Consequently, the VSNO may restrict access for new UEs to the network by raising the price of SLAs. In steady states 5 and 6, UEs consistently generate positive payoffs, leading them to adopt the purchase strategy. Furthermore, in steady state 5, $\Delta R_u > 0$, suggesting that VSNOs have sufficient spectrum resources. This may allow it to attract more UEs by reducing the price of SLAs.

Considering that the steady states remain constant in the game results and is unaffected by parameter changes, the analysis of the two dynamics presented above becomes more significant. In dynamic state 1, since the EEP is not a fixed value, when $x_3 = \frac{D_u - I_u}{\gamma_u I_u - I_u + D_u - \delta_u D_u} \to 1$, namely, VSNOs should strive to fulfill $\delta_u \to \frac{\gamma_u I_u}{D_u}$, while satisfying that x_3 belongs to (0, 1), a higher the number of UEs in group N favor the purchase strategy. In dynamic state 4, the range of values for the price adjustment rate δ_u can be calculated as follows:

$$x_3 = \frac{D_u - I_u}{\gamma_u I_u - I_u + D_u - \delta_u D_u} < x^*, \tag{29}$$

where x^* is the initial ratio of UEs to adopt the purchase strategy.

The equivalent transformation of (29) can be expressed as $\delta_u < \frac{(\gamma_u I_u - I_u + D_u)x^* - D_u + I_u}{D_u x^*}$. In practice, VSNOs need to attract more UEs to purchase their SLAs. However, prioritizing payoffs at the expense of serving an excessive number of UEs could significantly diminish the service experience for UEs. Therefore, VSNOs should strive to set δ_u close to its upper bound, as indicated in (30). This approach is intended to attract more UEs while ensuring a satisfactory service experience.

$$\delta_u \to \frac{(\gamma_u I_u - I_u + D_u)\, x^* - D_u + I_u}{D_u x^*} \tag{30}$$

By leveraging evolutionary game theory, VSNOs can dynamically adapt the prices of their SLAs by analyzing the purchasing preferences of UEs within the current network. Simultaneously, UEs can select more appropriate VSNOs and SLAs, guided by the VSNOs' pricing strategies. This interaction is expected to lead to the emergence of a dynamic equilibrium between them.

VI. Security Analysis and Discussion

In this section, we analyze the security of the proposed mechanism and compare the computational complexity of BEE.

A. Sharding Blockchain Security

In BEE, PMNOs, VSNOs, and UEs are all required to register with their real identities upon initial entry to the sharding blockchain. The sharding blockchain stores the hash values of this information, which ensures that even if the registration information is leaked, the attacker cannot access the user's real identity information to compromise privacy. Furthermore, if an attacker attempts to launch a Sybil attack by creating multiple identities, the system will recognize the identical hash values of the same information and reject the registration, thus resisting such attacks. More crucially, the proposed PoSP leverages the spectrum information of the VSNOs engaged in bookkeeping to reduce the mining difficulty of PoW, thereby minimizing the waste of computational resources. However, there is no compromise to the rationality and security of PoW. Therefore, it can be asserted that the overall security of PoSP is equivalent to that of PoW. Furthermore, the time limit for bookkeeping and the use of VRF-based random numbers in PoSP randomizes and makes the bookkeeping rights dynamic. Consequently, VSNOs with more spectrum resources are not guaranteed to always secure bookkeeping rights, effectively mitigating 51% attacks.

B. DSS Security

In BEE, all DSS information is encrypted and packaged into blocks on the sharding blockchain. Specifically, allocation information is confined to the allocation committee (PMNOs and VSNOs), and trading information to the service committee (VSNOs and UEs). The main chain only records block generation information, making it highly difficult for external eavesdroppers to obtain sensitive transaction details. To obtain DSS information, attackers must infiltrate PMNOs or VSNOs, which is a highly challenging task. Data integrity is ensured by the blockchain's inherent immutability, once a transaction is recorded in a block, altering it is computationally infeasible. Given the unique characteristics of spectrum resources, the SR must periodically track the transactions and utilization of spectrum resources to prevent misuse and unfair behaviors [9]. BEE provides the SR with a verifiable and secure audit using VRF for DSS across committees. BEE also effectively mitigates collusion attacks through the synergistic combination of its sharding structure, secure consensus mechanisms, and SR auditing. Double-spending of spectrum rights is prevented by the intra-shard PBFT consensus and the inter-shard PoSP consensus, ensuring that only one valid allocation of a given spectrum resource exists at any time.

C. Computational Complexity of TNSGA-III

In BEE, TNSGA-III enhances the diversity and convergence of the evolutionary results by dynamically and adaptively adjusting the mutation rate. However, this adjustment does not increase the overall computational complexity of the original NSGA-III. Specifically, under the condition of L optimization objective functions and a population size of X, the computational complexity of TNSGA-III is $\mathcal{O}(LX^2)$, which is superior to that of the spectrum allocation mechanisms in [30], [16], [21]. Moreover, while maintaining the same computational complexity, TNSGA-III can support more optimization objectives compared to the algorithm in [24], thus providing a more comprehensive spectrum allocation strategy for 6G networks.

VII. Simulation Results and Analysis

In this section, we first compare the proposed PoSP with traditional PoW. Then, we simulate the improvement in spectrum utilization using the proposed spectrum allocation scheme based on TNSGA-III. Finally, we investigate the evolution of strategy selection for UEs using evolutionary game theory. The configurations of critical parameters are detailed in Table V. The elliptic curve algorithm chosen for the experiments is secp256k1, a widely used curve in blockchain applications due to its balance between security and performance. Furthermore, ECC-secp256k1 and ECDSA-secp256k1 are employed for encryption/decryption and signing/verification of all information on the blockchain, respectively. SHA-256 is chosen to ensure the integrity and immutability of the blockchain data. When calculating the mining difficulty of PoSP using (4), we set $\alpha_1 = 0.5$, $\alpha_2 = 0.25$, and $\alpha_3 = 0.25$ to ensure that holders of superior spectrum resources are the most likely to obtain bookkeeping rights, as they are generally considered trustworthy. Simultaneously, the different weights reflect the importance of spectrum availability in the DSS mechanism. Similarly, we set $\beta_1 = 0.6$ and $\beta_2 = 0.4$ in (13), prioritizing data rate, as it is a more critical metric for 6G networks.

TABLE V
KEY PARAMETERS

Parameters	Values
Physical machine	Intel i5-8500@3.00GHz with 8GB RAM
Operating systems	Windows 11
Elliptic curve	secp256k1
Hash algorithm	SHA-256
Digital signatures	ECDSA (secp256k1)
Transmit power range [46]	20∼80 dBm
Data rate range [47]	10∼100 Gb/s
α_1, α_2, α_3; β_1, β_2	0.5, 0.25, 0.25; 0.6, 0.4

A. Simulation of Proposed PoSP

In this part, we validate the superiority of PoSP by comparing it with PoW implemented in Golang Language 1.19.2. In this simulation, the $target$ is a 256-bit number (i.e., 64 hexadecimal digits, with each hexadecimal digit representing a nibble), for example, 0000 0a10 f68c 904d e697 4806 1349 e5d6 a3a0 bf48 015f dd0e ea45 b393 f275 4c30. The number of leading zeros indicates the mining difficulty, more zeros represent a smaller $target$ and a higher mining difficulty. We set the mining difficulty to 20, which means the $target$ must have at least 5 leading zeros. Each algorithm is tested 100 times, and the average is calculated every 10 tests to mitigate the impact of hardware fluctuations on the results. VSNOs participating in the consensus are considered as nodes. When consensus is reached among nodes to package a new block, it indicates that an equivalent number of VSNOs in the sharding blockchain have reached an inter-shard consensus. The relationship between the number of nodes and consensus time, as well as between the number of nodes and transaction throughput, are tested to verify the efficiency of PoSP.

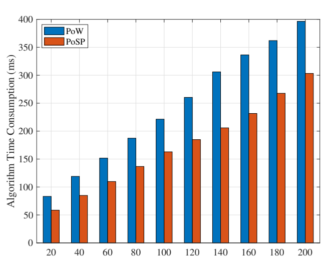

Fig. 4. ATC comparison.

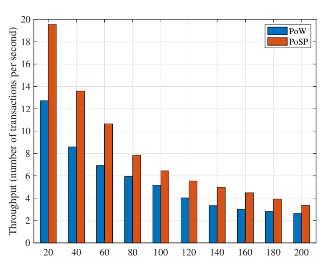

Fig. 5. ATT comparison.

First, we test the average time consumption (ATC) for both algorithms to reach consensus. As shown in Fig. 4, PoSP achieved a maximum reduction of 32.73% in ATC compared to PoW. Furthermore, as the number of nodes increases, the increase in ATC of PoSP is smaller than that for PoW. This ensures that computational resources are not excessively wasted during the consensus process. Since PoSP reduces the mining difficulty by incorporating the spectrum holdings of PMNOs and VSNOs, it achieves consensus more efficiently, significantly reducing ATC.

Then, we compare the average transaction throughput (ATT) for both algorithms in terms of transactions per second. The results are presented in Fig. 5. As the number of nodes increases, the time required to reach consensus also increases, resulting in a decrease in ATT for both algorithms. However, the advantage of PoSP remains evident, as it achieves a maximum increase of 58.10% in ATT compared to PoW. The main reason for this result is that the ATC of PoSP is relatively small, enabling it to process more transactions per unit of time.

B. Simulation of Proposed Spectrum Allocation Scheme

In this part, to validate the improvement in spectrum utilization achieved by the TNSGA-III-based spectrum allocation scheme, we evaluate its performance using the PlatEMO platform [48].

Since NSGA-II struggles to handle MOOPs with more than three objectives, we firstly use Generational Distance (GD) [49] and Hypervolume (HV) [50] to compare the performance of TNSGA-III and NSGA-III on the proposed MOOPs. Fig. 6 shows that the GD value of TNSGA-III decreases faster and eventually stabilizes at a lower value, indicating that TNSGA-III exhibits stronger convergence. Fig. 7 shows that the HV value of TNSGA-III increases faster than that of NSGA-III, and eventually stabilizes at a higher value, indicating that TNSGA-III also exhibits better diversity. This further demonstrates that the enhanced convergence and diversity of TNSGA-III make it easier to find the optimal solution for the spectrum allocation MOOP.

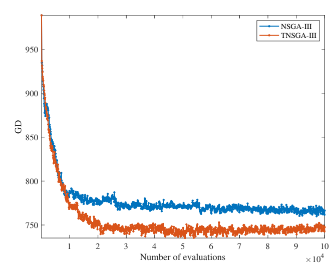

Fig. 6. GD comparison.

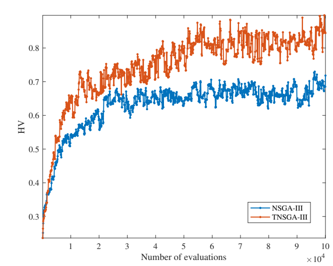

Fig. 7. HV comparison.

In evolutionary algorithms, the population size influences the diversity of solutions, while the number of iterations impacts the quality of solutions. Then, we model the DSS problem as a MOOP based on the envisioned communication capabilities of 6G [46], [47], and conduct tests to examine changes in subbands occupancy, data rate, transmit power, and PMNOs' revenue. The chromosomes consist of 100 genes representing subbands, and the tests are performed by varying the population size and the number of iterations. The proposed scheme selects the best solution from the final optimal solution set using TOPSIS. Due to the randomness inherent in evolutionary algorithms, we analyze both the optimal solution and the average performance of the population before and after evolution, comparing them in terms of their improvement rates.

The improvement rate of subbands occupancy under TNSGA-III is shown in Fig. 8. Overall, the average subbands occupancy improvement rate increases with the growth of both population size and the number of iterations. This indicates that to achieve the best spectrum allocation, it is beneficial to increase both the population size and the number of iterations as much as is computationally feasible. In the comparison of optimal solutions, the improvement rate shows irregular variations because TOPSIS considers the other three objectives simultaneously. However, the minimum improvement rate (achieved with a population size of 100 and 800 iterations) still reaches 94.44%.

As subbands occupancy increases, Fig. 9, Fig. 10, and Fig. 11 illustrate the variations in the other three objectives with changes in population size and the number of iterations, respectively. Overall, as the average subbands occupancy improvement rate increases, the data rate of the entire network is expected to rise, leading to higher transmit power and an increase in PMNOs' revenues. To simulate various scenarios for different frequency bands in the future 6G networks, we differentiate the data rate, transmit power, and revenue for each subband in this experiment. Consequently, the other three objectives do not change in tandem with subbands occupancy in the comparison of the optimal solutions. At the minimum improvement rate of subbands occupancy, the corresponding data rate, transmit power, and PMNOs' revenues increased by 1.84 times, 1.61 times, and 5.0 times, respectively. This demonstrates the effectiveness of our proposed scheme in optimizing spectrum utilization while enhancing network performance and operator revenues.

C. Simulation of Proposed Spectrum Trading Scheme

In this part, we aim to assess the impact of various parameters on the game. We conduct simulations of both the steady state and dynamic evolution of the proposed spectrum trading game model with different adjustment rates and initial purchase ratios, using MATLAB 2023b.

1) Steady State: The proposed game model consists of four steady states. We simulate the evolution of these four states with different adjustment rates and initial purchase ratios, as shown in Fig. 12. In steady states 2 ($\gamma_u = 0.6$, $\delta_u = 0.8$, $I_u = 8$, $D_u = 10$) and 3 ($\gamma_u = 0.6$, $\delta_u = 1.2$, $I_u = 8$,

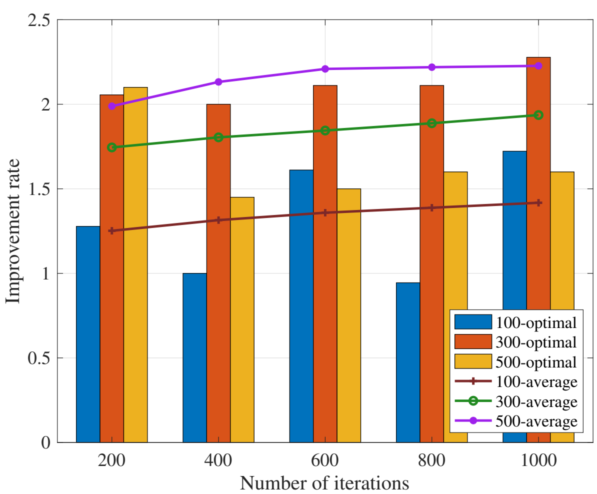

Fig. 8. The improvement rate of subbands occupancy.

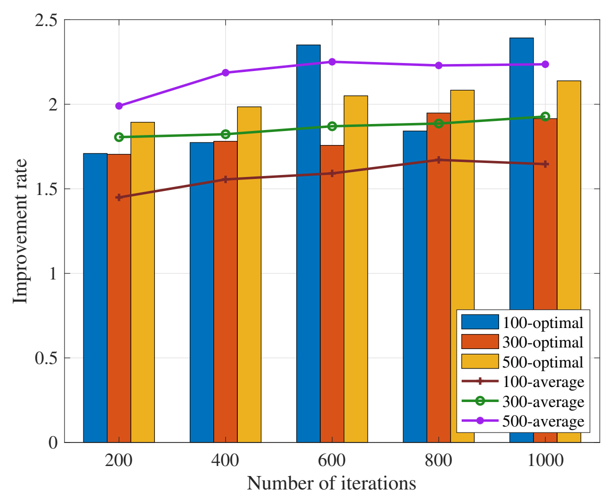

Fig. 9. The improvement rate of data rate.

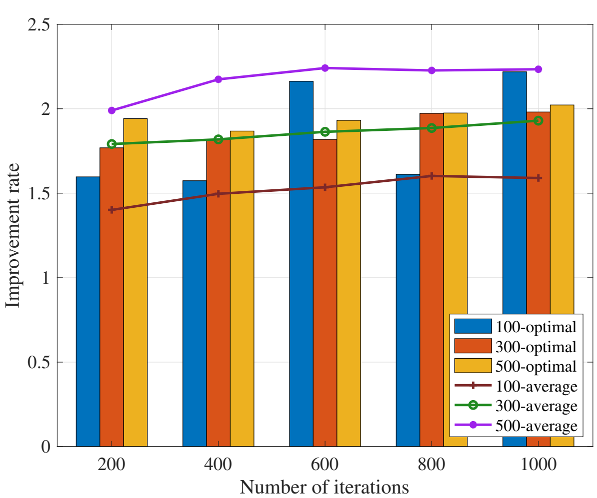

Fig. 10. The improvement rate of transmit power.

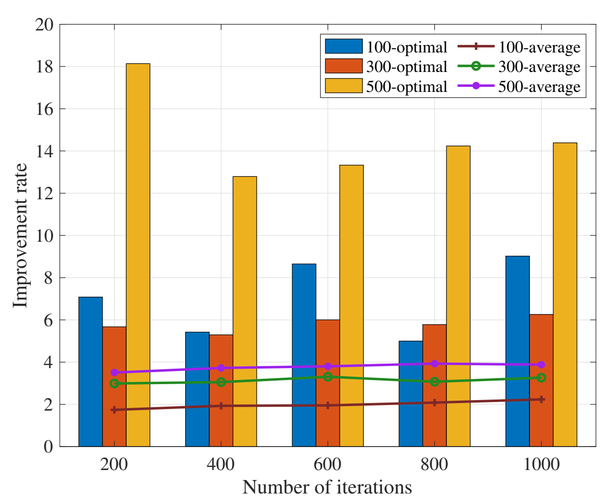

Fig. 11. The improvement rate of PMNOs' revenues.

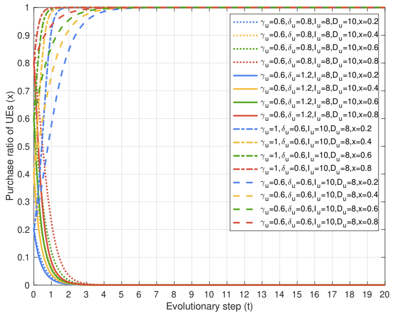

Fig. 12. Evolutionary graph of four steady states.

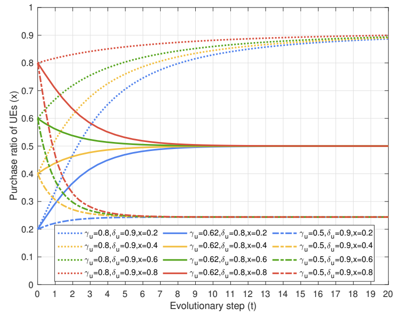

Fig. 13. Evolutionary graph of dynamic state 1.

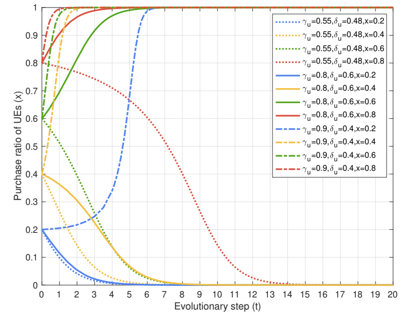

Fig. 14. Evolutionary graph of dynamic state 2.

$D_u = 10$), even with an initial purchase ratio of 0.8, the strategies of the UEs eventually evolve to not purchase due to the unaffordability of high SLAs. It can be observed in state 3 that VSNOs deliberately set $\delta_u > 1$ to prevent further deterioration of the spectrum resource burden. In steady state 5 ($\gamma_u = 1$, $\delta_u = 0.6$, $I_u = 10$, $D_u = 8$), VSNOs have sufficient spectrum resources, thus lowering the price of SLAs to attract more UEs and prompting the strategies of UEs to eventually evolve to purchase. Similarly, in state 6 ($\gamma_u = 0.6$, $\delta_u = 0.6$, $I_u = 10$, $D_u = 8$), although the service experience of UEs is slightly affected due to the burden of spectrum resources of VSNOs, VSNOs subsidize the UEs by lowering the prices of the SLAs. As a result, the UEs' $RE_u > 0$ during this time, leading to their final evolutionary strategy evolving to purchase. Therefore, VSNOs should consider the current spectrum resources situation, as well as the payoffs of UEs, and dynamically adjust δ_u to guide the UEs to independently choose the appropriate strategy.

2) Dynamic State: The proposed game model includes two dynamic states. To validate the evolution of these two states to support VNSOs in guiding UEs' dynamic adjustment strategies, we simulate the evolution of these two dynamics with different adjustment rates and initial purchase ratios.

In dynamic state 1 ($I_u = 10$, $D_u = 9$, the values of γ_u and δ_u are shown in Fig. 13), x_3 represents the ratio of UEs choosing to purchase in the evolution results. Fig. 13 shows the simulation results, indicating that regardless of changes in the value of δ_u, the final evolution result converges to a specific ratio rather than leading to purchase or not purchase. However, as δ_u increases, the ratio of UEs choosing the purchase strategy also increases. Notably, when δ_u is fixed, interactions occur between groups with high initial purchase ratios and those with low initial purchase ratios, confirming that the choices of UEs regarding VSNOs and SLAs affect each other. Therefore, in this state, VSNOs should maximize δ_u to attract a limited number of new UEs while maintaining service quality for the existing UEs.

In dynamic state 4 ($I_u = 9$, $D_u = 10$, the values of γ_u and δ_u are in Fig. 14) , UEs with initial purchase ratio $x \in (0, x_3)$ evolve to not purchase, while those with initial purchase ratio $x \in (x_3, 1)$ evolve to purchase. Fig. 14 shows the simulation results. When $\gamma_u = 0.55, \delta_u = 0.48$, the final evolution result is not purchase, regardless of the initial purchase ratio. When $\gamma_u = 0.8, \delta_u = 0.6$, the initial purchase ratios x of 0.6 and 0.8 evolve to purchase, while the other ratios ultimately evolve to not purchase. When $\gamma_u = 0.9, \delta_u = 0.4$, all situations eventually evolve to purchase. In this state, UEs have $RN_u < 0; RE_u > 0; \Delta R_u > 0$, that is, at this time, UEs have negative payoff in general cases, which proves that VSNOs have overpriced their SLAs and need to make price adjustment. Meanwhile, VSNOs can balance their breakeven point by slightly reducing service quality of current service UEs to attract some new UEs.

VIII. Conclusion

This article proposes BEE, a novel secure DSS mechanism designed for service-centric networks in 6G. A sharding blockchain serves as infrastructure to record the information on spectrum sharing, allocation, and transactions, while the proposed PoSP is employed to mitigate computational resource waste. Leveraging TNSGA-III, we construct dynamic and fine-grained spectrum allocation schemes for both PMNOs and VSNOs. Furthermore, we design a price-guided spectrum trading mechanism between VSNOs and UEs to implement a two-stage, full-flow DSS mechanism. For future work, we will focus on evaluating the performance of BEE under conditions of increasing network scale and user density, while simultaneously optimizing and enhancing the evolutionary efficiency of the TNSGA-III algorithm and exploring more secure and reliable consensus mechanisms to improve consensus efficiency. Moreover, we will investigate the application of BEE to other network resources, fully realizing the potential of BEE in 6G networks.

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Kun Yan received the B.S. degree in Internet of Things Engineering from Xi'an University of Technology, Xi'an, China, in 2019, He is currently working toward a Ph.D. degree in the School of Telecommunications Engineering, Xidian University. His research interests include 6G networks, resource management, and blockchain.

Wenping Ma received the B.S. and M.S. degrees in Fundamental Mathematics from Shaanxi Normal University, Xi'an, China, in 1987 and 1990, respectively, and the Ph.D. degree in Communication and Information System from Xidian University, Xi'an, in 1999, where he is currently a Full Professor with the School of Telecommunications Engineering. His current research interests include information theory, communication theory, blockchain, and 6G networks security.

Shaohui Sun received his Ph.D. from Xidian University, Xi'an, China, in 2003. Since January 2011, he has been the Chief Technical Officer with Datang Wireless Mobile Innovation Center of the Datang Telecom Technology and Industry group, where he has been deeply involved in the development and standardization of the Third-Generation Partnership Project Long-Term Evolution (3GPP LTE). His current research interest includes advanced technologies related to B5G/6G.

Weiwei Wang received the B.S. degree in Mathematics from Baicheng Normal University, Jilin, China, in 2018, and the M.S. degree in 2021 in the school of mathematics at Liaoning University, Liaoning, China. He is currently pursuing the Ph.D. degree in the School of Communication Engineering, Xidian University, Xi'an, China. His research interest includes information security, cryptography.