Multi-Objective Spectrum Allocation and Power Control in Cognitive Radio Networks: Postprint

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Abstract

This paper investigates the power control problem in cognitive radio networks employing Underlay access, proposing a framework that simultaneously considers both spectrum allocation and power control. To simultaneously satisfy diverse user requirements, network capacity and power efficiency are formulated as a multi-objective optimization problem. An improved multi-objective optimization algorithm based on NSGA-II is then proposed to model and solve this problem, obtaining a Pareto optimal solution set that accommodates different user needs. Finally, the proposed method is experimentally compared with the SPEA-II algorithm. Simulation results demonstrate that the proposed method can effectively search for optimal solutions and satisfy spectrum and power allocation requirements under various scenarios.

Full Text

Preamble

Spectrum Allocation and Power Control with Multi-Objective Optimization in Cognitive Radio Networks

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Abstract: This paper investigates the power control problem in cognitive radio networks based on the Underlay access method, considering both spectrum allocation and power control simultaneously. To satisfy multiple user requirements concurrently, network capacity and power consumption efficiency are formulated as a multi-objective optimization problem. An improved multi-objective optimization algorithm based on NSGA-II is proposed to solve this problem, yielding a Pareto optimal solution set suitable for different user needs. Finally, the proposed method is compared with the SPEA-II algorithm through experiments. Simulation results demonstrate that the proposed approach can effectively search for optimal solutions and meet the requirements of spectrum and power allocation under various conditions.

Keywords: cognitive radio; spectrum allocation; power control; multi-objective optimization

0 Introduction

The rapid development of wireless communication technologies and the explosive growth of wireless applications have led to increasing demand for radio spectrum resources. In contrast, radio spectrum is managed by government or international agencies through fixed allocation policies, which permanently assign spectrum to licensed holders. This allocation approach results in significant temporal and spatial variations in spectrum utilization, ranging from approximately 15% to 85%, leaving large portions of licensed spectrum underutilized. To address this severe imbalance in spectrum utilization and make full use of spectrum resources, Mitola first proposed the concept of cognitive radio. He envisioned cognitive radio as an intelligent software-defined radio that not only possesses parameter reconfiguration capabilities but can also perceive its surrounding environment to provide wireless resources and services that meet user demands.

In cognitive radio networks, unlicensed users, known as secondary users, can intelligently sense and access idle licensed frequency bands without interfering with the normal communications of licensed primary users, thereby achieving efficient spectrum utilization. Consequently, compared to traditional networks, cognitive radio can obtain more available spectrum segments to enhance network performance and capacity. Cognitive radio technology allocates available spectrum resources to users to achieve efficient utilization, making spectrum allocation a critical component of cognitive radio systems. Spectrum allocation techniques can assign currently available frequency bands to users based on the number of users accessing the network and their service requirements, enabling cognitive users to share spectrum resources in a reasonable and fair manner without causing excessive interference to primary users. Since spectrum allocation directly impacts network performance metrics, cognitive radio systems typically acquire appropriate spectrum allocation schemes according to user performance requirements. However, network performance metrics are often mutually constrained; optimizing a single metric in isolation may degrade other aspects of performance. Users generally do not pursue the optimization of a single performance indicator but rather seek a balance among multiple metrics. Therefore, researchers have recently begun applying multi-objective optimization methods to spectrum allocation in cognitive radio to achieve balanced network performance.

For instance, reference [5] formulated the spectrum allocation problem in underlay spectrum sharing networks as a multi-objective optimization problem to maximize throughput and spectrum efficiency, using the NSGA-II algorithm to search for Pareto optimal solutions. Reference [6] employed a multi-objective genetic algorithm with a graph coloring spectrum allocation model to maximize system utility and proportional fairness among secondary users, achieving dynamic allocation of idle spectrum among secondary users in cognitive radio networks.

Secondary user access to licensed spectrum must first ensure no impact on primary user communications and second minimize interference to co-channel secondary users to achieve good network performance. Achieving these objectives requires power control for secondary users, as optimized power allocation strategies can guarantee secondary user transmissions while controlling interference to other users. Therefore, power control is crucial for optimizing cognitive radio network performance, and researchers have extensively studied multi-objective optimization problems in power control. Reference [7] optimized parameter adaptation for OFDM-based cognitive radio engines using the cat swarm optimization concept, considering spectrum interference between primary and secondary users, and proposed a fuzzy logic-based strategy to find compromise solutions on the Pareto front. Reference [8] introduced a new performance metric called interference efficiency, representing the number of bits transmitted per unit of interference energy imposed on primary user receivers. The interference efficiency optimization problem was solved by optimizing multiple objectives: maximizing the ergodic sum rate of multiple cognitive users while minimizing interference to primary users. To improve energy efficiency in cognitive radio networks, reference [9] proposed jointly maximizing ergodic capacity while minimizing average transmission power. Reference [10] studied optimal link adaptation in OFDM-based cognitive radio systems, formulating it as two conflicting objectives: maximizing system throughput and minimizing transmission power, optimizing bit and power allocation for each cognitive user subcarrier under constraints of predetermined interference thresholds for primary users and spectrum sensing errors. In reference [11], the authors applied cross-entropy optimization to joint multi-relay assignment and source/relay power allocation in green cooperative cognitive radio networks, using a Monte Carlo-based cross-entropy optimization algorithm to optimize two conflicting objectives: maximizing overall rate in GCCR networks and minimizing greenhouse gas emissions.

The aforementioned literature considered either spectrum or power when optimizing multiple network performance metrics, overlooking the fact that both simultaneously affect network performance. Therefore, this paper addresses both spectrum and power for secondary users in cognitive radio networks, adjusting secondary user transmission power and operating frequency bands to ensure normal communications for all users. To this end, we propose a genetic algorithm-based multi-objective optimization algorithm to solve the joint spectrum allocation and power control problem in cognitive radio, achieving a balance between maximum power consumption efficiency and maximum network capacity.

1 System Model

We consider a cognitive wireless network model comprising several communication links, as shown in [Figure 1: see original paper]. In this network, communication links with primary users as receivers are called primary links, while those with secondary users as receivers are called secondary links, coexisting within a common region.

All primary users in the network are served by their respective transmitters with fixed locations. In secondary links, each transmitter serves only one secondary user, randomly distributed within the region. This paper adopts the Underlay spectrum access method, allowing primary and secondary users to simultaneously use a particular frequency band. That is, under the premise of not affecting normal communications for all users in the network, the same frequency band can be assigned to one or multiple secondary links.

1.1 Cognitive Radio Network Model

Given the coexistence of primary user networks and cognitive radio networks, our model divides the entire network into two parts: a communication network containing primary users and one containing secondary users, denoted as the primary network and secondary network, respectively, represented by $\mathcal{P}$ and $\mathcal{S}$. We define sets $\mathcal{M}$, $\mathcal{PL}$, and $\mathcal{SL}$, where $\mathcal{M}$ is the set of channels that can be allocated in the current network, while $\mathcal{PL}$ and $\mathcal{SL}$ represent the sets of all primary links in the primary network and all secondary links in the secondary network, respectively.

In this network model, the transmission performance of both primary and secondary links is affected by the transmission power of all users in the current frequency band. Specifically, primary links experience interference from secondary links operating in the same band, while secondary links are affected by both primary links and other secondary links in the same band. Therefore, to ensure overall network performance, we must evaluate the transmission quality of all links in the network. In wireless network transmissions, Signal-to-Interference-plus-Noise Ratio (SINR) is typically used to measure received signal quality. SINR is defined as the ratio of expected signal reception power at the receiver to the sum of unintended signal (interference) reception powers from other links on the same channel.

Using the example in [Figure 1: see original paper], primary link 1 operates on channel m_1, with secondary links 1 and 2 transmitting data on the same channel. Therefore, while primary link receiver V_{R1}^p receives signals from transmitter V_{S1}^p, it also receives signals from secondary link transmitters U_{S1}^s and U_{S2}^s. Similarly, secondary link receivers U_{R1}^s and U_{R2}^s experience interference not only from each other' s transmitters but also from primary link transmitter V_{S1}^p when receiving signals from their respective transmitters.

Based on these definitions, we first calculate the expected reception power for primary link pl operating on channel m:

$$\mathcal{P}_{pl,m}^{S,R} = G(V_{S,pl}^{p}, V_{R,pl}^{p}) \cdot P_{pl}^{p}$$

where $V_{S,pl}^{p}$ and $V_{R,pl}^{p}$ represent the transmitter and receiver of primary link pl, respectively, and P_{pl}^{p} denotes the transmission power of this transmitter. $G(V_{S,pl}^{p}, V_{R,pl}^{p})$ represents the path loss from transmitter $V_{S,pl}^{p}$ to its receiver $V_{R,pl}^{p}$:

$$G(V_{S,pl}^{p}, V_{R,pl}^{p}) = k \cdot d(V_{S,pl}^{p}, V_{R,pl}^{p})^{-\alpha}$$

where k and α are the path loss constant and exponent, respectively, and $d(V_{S,pl}^{p}, V_{R,pl}^{p})$ is the distance from $V_{S,pl}^{p}$ to $V_{R,pl}^{p}$.

This paper assumes that all primary links in the current region operate on different communication channels. Therefore, when calculating unintended signal reception power, we only need to consider the sum of interference from all secondary link transmitters operating on channel m to this primary user, in addition to thermal noise at the receiving device:

$$\mathcal{I}_{pl,m}^{S,R} = \sum_{sl \in \mathcal{SL}} G(V_{S,pl}^{p}, U_{R,sl}^{s}) \cdot P_{sl}^{s} \cdot \mathcal{I}_{sl,m}$$

where $\mathcal{I}_{sl,m}$ indicates whether secondary link sl operates on channel m.

Based on equations 错误! 未找到引用源。~ 错误! 未找到引用源。, the SINR for primary users operating on channel m can be expressed as:

$$\text{SINR}_{pl,m} = \frac{\mathcal{P}_{pl,m}^{S,R}}{\mathcal{I}_{pl,m}^{S,R} + \mathcal{N}_{pl,m}}$$

where constant $\mathcal{N}_{pl,m}$ represents thermal noise at the device. In essence, this equation shows the signal strength that primary user pl can receive, while $\mathcal{I}_{pl,m}^{S,R} + \mathcal{N}_{pl,m}$ defines the total interference experienced by this user, where $\mathcal{I}_{pl,m}^{S,R}$ represents the sum of interference from all secondary links using the same channel.

When performing spectrum allocation and power control, the network must not only ensure normal communications for primary users but also minimize interference among secondary users operating on the same channel. Therefore, we must consider the SINR of all secondary users. When calculating SINR for secondary users, signals from all primary and secondary links operating on the same channel constitute interference and must be considered separately. First, we consider the interference from primary link pl operating on channel m to secondary link sl:

$$\mathcal{I}_{sl,pl,m}^{S,R} = G(U_{S,sl}^{s}, V_{R,pl}^{p}) \cdot P_{pl}^{p}$$

Similarly, interference from all other secondary links operating on channel m to the current secondary link can be defined as:

$$\mathcal{I}_{sl,sl,m}^{S,R} = \sum_{\substack{sl_i \in \mathcal{SL} \\ sl_i \neq sl}} G(U_{S,sl}^{s}, U_{R,sl_i}^{s}) \cdot P_{sl_i}^{s} \cdot \mathcal{I}_{sl_i,m}$$

The expected signal reception power for this secondary user can be defined as:

$$\mathcal{P}_{sl,m}^{S,R} = G(U_{S,sl}^{s}, U_{R,sl}^{s}) \cdot P_{sl}^{s}$$

Therefore, the SINR for this user can be obtained through:

$$\mathrm{SINR}_{sl,m} = \frac{\mathcal{P}_{sl,m}^{S,R}}{\mathcal{I}_{sl,pl,m}^{S,R} + \mathcal{I}_{sl,sl,m}^{S,R} + \mathcal{N}_{sl,m}}$$

1.2 Optimization Objectives

As described above, with the coexistence of primary and secondary users in the network, spectrum allocation and power control significantly impact network performance. Therefore, to ensure overall network performance, we must establish network objectives based on requirements. This paper adopts the Underlay spectrum access method, allowing secondary users to access licensed frequency bands currently used by primary users. In this scenario, interference from secondary users to primary users must remain within tolerable limits. Consequently, secondary link transmission power is the main cause of network interference. While reducing secondary link transmission power can decrease interference to primary users, blindly reducing power cannot guarantee network communication performance. Therefore, reasonable power control can both prevent serious interference to primary users and ensure communication performance for secondary users. Thus, when performing spectrum allocation in Underlay scenarios, we can further consider power control to achieve network performance optimization through joint allocation of both resources. Spectrum allocation and power control affect multiple network performance metrics, and to achieve balanced optimization among these metrics, we formulate the problem as a multi-objective optimization problem to maximize network power consumption efficiency and system capacity.

1.2.1 Power Consumption Efficiency Power control is one of the most critical issues in wireless communication networks. It not only reduces interference among network users but also saves power consumption of network equipment, providing guarantees for sustained device operation. This paper assumes that secondary link transmitters can adjust their transmission power downward from their maximum power. Therefore, we propose the performance metric of power consumption efficiency, defined as the ratio of power saved from the maximum power to the maximum power itself, as shown in equation 错误! 未找到引用源。:

$$f_1 = \frac{\sum_{sl \in \mathcal{SL}} (P_{\text{Max}} - P_{sl}^s)}{|\mathcal{SL}| \cdot P_{\text{Max}}}$$

where P_{sl}^s represents the current transmission power of the transmitter in secondary link sl, and P_{Max} represents the maximum transmission power of this transmitter.

1.2.2 Network Capacity This paper defines network capacity as the total data rate of the entire network, i.e., the sum of data rates obtained by all primary and secondary links. Its magnitude primarily depends on the bandwidth of shared channels and the current communication environment (such as attenuation and interference). Based on Shannon' s model [12], we present capacity formulas for primary and secondary links:

$$C_{pl} = W \log_2(1 + \text{SINR}_{pl,m})$$

$$C_{sl} = W \log_2(1 + \text{SINR}_{sl,m})$$

where C_{pl} and C_{sl} represent the data rates of primary link pl and secondary link sl, respectively, and W denotes the bandwidth of the shared channel. This paper assumes that all frequency bands participating in allocation have identical bandwidth. From equation 错误! 未找到引用源。, we derive the total network capacity:

$$f_2 = \sum_{pl \in \mathcal{PL}} C_{pl} + \sum_{sl \in \mathcal{SL}} C_{sl}$$

1.3 Optimization Problem Formulation

As discussed above, increasing secondary link transmission power reduces network power consumption efficiency but does not necessarily improve network capacity, because higher power also increases network interference. Therefore, power consumption efficiency and network capacity are two conflicting objectives suitable for multi-objective optimization. Based on equations 错误! 未找到

引用源。and 错误！未找到引用源。, we define this problem as the multi-objective optimization problem shown in equation 错误！未找到引用源。:

$$\begin{aligned} \max \quad & f_1 = \frac{\sum_{sl \in \mathcal{SL}} (P_{\text{Max}} - P_{sl}^{s})}{|\mathcal{SL}| \cdot P_{\text{Max}}} \\ \max \quad & f_2 = \sum_{pl \in \mathcal{PL}} C_{pl} + \sum_{sl \in \mathcal{SL}} C_{sl} \\ \text{s.t.} \quad & \text{SINR}_{pl} \geq \beta_{pl}, \quad \forall pl \in \mathcal{PL} \\ & \text{SINR}_{sl} \geq \beta_{sl}, \quad \forall sl \in \mathcal{SL} \end{aligned}$$

Interference from ambient noise or other radio transmissions can degrade SINR at receivers, representing an important factor affecting network communication stability. Therefore, to guarantee Quality of Service (QoS), SINR generally must exceed a certain threshold. To this end, we incorporate SINR constraint conditions for communication links in equation 错误！未找到引用源。, where β_{pl} and β_{sl} represent the SINR thresholds for primary link pl and secondary link sl, respectively.

2 Multi-Objective Spectrum Allocation and Power Control Algorithm

The multi-objective optimization problem defined in equation 错误！未找到引用源。is relatively complex, requiring substantial computational cost when searching for spectrum and power allocation schemes. However, spectrum and power allocation must quickly and efficiently provide allocation schemes based on current environmental conditions and performance requirements, necessitating the design of effective heuristic algorithms to obtain optimal solutions. To rapidly acquire optimal solutions, this paper selects the elitism-based Non-dominated Sorting Genetic Algorithm II [13] (NSGA-II) to solve the multi-objective optimization problem defined in equation 错误！未找到引用源。.

NSGA-II is an improved version of the Non-dominated Sorting Genetic Algorithm [14] (NSGA). Both are multi-objective optimization algorithms based on the Pareto optimality concept. Compared to algorithms not based on Pareto optimality (such as the Vector Evaluated Genetic Algorithm [15] (VEGA)), NSGA-II overcomes the disadvantage of easily falling into local optima and can effectively search the entire feature space. The algorithm proposes a fast non-dominated sorting method that efficiently ranks all solutions in the population and classifies them into multiple non-dominated fronts. Compared to NSGA, its computational complexity is reduced from $\mathcal{O}(mN^3)$ to $\mathcal{O}(mN^2)$, where m is the number of objective functions and N is the population size. Additionally, the algorithm introduces an elite preservation strategy that combines parent and offspring populations to compete for the next generation, ensuring that certain excellent population individuals are not discarded during evolution. Consequently, as the algorithm iterates continuously, excellent individuals increase rapidly, thereby improving optimization result precision.

This paper improves NSGA-II to handle the multi-objective optimization problem defined in equation 错误! 未找到引用源。. To solve this problem, we first need to encode spectrum and power allocation schemes, as shown in [Figure 2: see original paper]. When encoding spectrum allocation schemes, we define vector $\mathbf{c} = (c_1, c_2, \dots, c_{|\mathcal{SL}|})$, where c_i represents the channel number assigned to secondary link i, with c_i taking integer values in the range $[1, |\mathcal{M}|]$. Additionally, while allocating channels to secondary links, we must also perform power allocation. Similarly, we define vector $\mathbf{p} = (p_1, p_2, \dots, p_{|\mathcal{SL}|})$, where p_i represents the transmission power of transmitter S_i^s in secondary link i, with p_i also taking integer values in the range $[1, P_{\text{Max}}]$.

In [Figure 2: see original paper], f_1 and f_2 are objective values calculated based on $\mathbf{c}$, $\mathbf{p}$, and equation 错误! 未找到引用源。. When seeking optimal solutions, the proposed algorithm first performs non-dominated sorting on the entire population. The non-dominated sorting algorithm compares the two objective values of each individual with those of other individuals to determine the dominance relationship among individuals. In the network scenario considered in this paper, for any two individuals p and q in the population, p dominates q if their objective values satisfy any of the conditions in equation 错误! 未找到引用源。:

$$\begin{aligned} & f_1(p) > f_1(q) \text{ and } f_2(p) > f_2(q) \\ \text{or } & f_1(p) > f_1(q) \text{ and } f_2(p) = f_2(q) \\ \text{or } & f_1(p) = f_1(q) \text{ and } f_2(p) > f_2(q) \end{aligned}$$

where $f_1(\cdot)$ and $f_2(\cdot)$ represent the values of the first and second objectives for the corresponding individual, respectively.

The algorithm then uses the dominance relationship among individuals to assign ranks, with the rank of each individual represented by r in [Figure 2: see original paper]. The set of individuals with the highest rank constitutes the Pareto optimal solution set, also known as the Pareto front. The specific steps to obtain the Pareto front are as follows:

a) For each individual p, compare its objective values with those of other individuals sequentially to determine the number of individuals in the population that dominate p, denoted as n_p. Simultaneously, add the individuals dominated by p to set S_p;

b) Assign rank 1 to all individuals in the population with $n_p = 0$, and simultaneously perform the Pareto optimality operation on individuals in set S_p;

c) Repeat step b) to generate the next rank.

In [Figure 2: see original paper], d represents crowding distance, which indicates the density of other individuals distributed around this individual in the population. In the algorithm, crowding distance calculation is a crucial component for maintaining population diversity within the same non-dominated rank. Based on the concept of crowding distance from reference [13], the crowding distance of individual i can be calculated by:

$$d_i = \sum_{k=1}^{2} \frac{f_k^{(i+1)} - f_k^{(i-1)}}{f_k^{\max} - f_k^{\min}}$$

where $f_k^{(i+1)}$ and $f_k^{(i-1)}$ represent the k-th objective values of the individuals immediately after and before individual i within the same non-dominated rank, respectively. $f_k^{\max}$ and $f_k^{\min}$ denote the maximum and minimum values of the k-th objective in the current non-dominated front.

In summary, based on the individual encoding structure shown in [Figure 2: see original paper], the algorithm is applied to the spectrum allocation and power control problem to obtain Pareto optimal solutions. The detailed process is as follows:

a) Randomly initialize a population P_t of size N;

b) Perform ranking operation on P_t using the non-dominated sorting algorithm, while calculating its crowding distance;

c) Select excellent individuals from P_t through binary tournament selection for crossover and mutation operations to generate a new population Q_t;

d) Combine populations P_t and Q_t to create the combined population R_t;

e) Perform ranking operation on R_t using the non-dominated sorting algorithm, while calculating its crowding distance. Select the top N optimal individuals based on non-dominated rank and crowding distance to form population P_{t+1};

f) If termination conditions are not met, jump to step (2) to continue execution.

After the final iteration, select the individuals with the highest dominance rank from P_{t+1} to form the Pareto front. Consequently, the Pareto front is a set of optimal solutions, where each solution corresponds to a spectrum allocation and power control scheme.

3 Simulation and Results Analysis

To evaluate the performance of the proposed multi-objective optimization algorithm in solving the problem defined by equation 错误! 未找到引用源。, this section conducts simulation verification for different network requirements. The simulation network is shown in [Figure 3: see original paper]: 20 secondary links are randomly distributed in a 3000m×3000m region, with the distance between secondary link transmitters and receivers limited to within 120 meters. Additionally, 4 primary links are fixed in the region, using mutually non-interfering channels, and all allocatable channels have a bandwidth of 5MHz. Since we assume channel strength is determined solely by path fading, we define the path loss constant $k = 3$ and path fading exponent $\alpha = 4$ according to the path fading definition given in equation 错误！未找到引用源。. To simplify calculations, we assume the maximum transmission power of secondary link transmitters is 5mW, which can be adjusted to any integer power between 1-5mW. We also assume all links have the same SINR threshold, i.e., $\beta_{pl} = \beta_{sl} = \beta$.

[Figure 4: see original paper] shows the results of running the proposed algorithm 10 times with an SINR threshold of 4dB. From the distribution of optimal solutions in the figure, we can observe that power consumption efficiency and network throughput are mutually conflicting performance metrics; improvements in network throughput typically come at the cost of reduced power consumption efficiency. However, further analysis of experimental results reveals that while power consumption efficiency increases substantially, the reduction in network throughput is relatively small, approximately around 20%. This occurs because in cognitive radio networks, the same channel is assigned to multiple links, and when these links transmit simultaneously, severe co-channel interference occurs, causing network capacity to drop sharply. Consequently, blindly increasing transmission power does not significantly improve network throughput. However, in network scenarios requiring energy conservation, we can choose to substantially improve power consumption efficiency while moderately increasing network throughput to achieve energy savings.

To further evaluate the performance of the proposed algorithm, we employ the improved Strength Pareto Evolutionary Algorithm [16] (SPEA-II) to solve the multi-objective spectrum allocation problem for comparison. SPEA-II is recognized as an effective elitist multi-objective evolutionary algorithm that has demonstrated high efficiency in solving MOP problems in wireless networks [17, 18]. [Figure 5: see original paper] shows the results of running SPEA-II 10 times with an SINR threshold of 4dB. Compared with [Figure 5: see original paper], SPEA-II finds some solutions in the low power consumption efficiency range (10%-20%) but performs weakly when searching for effective solutions between 20%-40% and 70%-80%. In contrast, as shown in [Figure 4: see original paper], the Pareto front obtained by our proposed algorithm in each run is very evenly distributed. This benefit arises because during individual selection, the algorithm tends to select non-dominated individuals with larger crowding distances as offspring, thereby strengthening the search in sparser regions of the current Pareto front and enabling solutions to spread uniformly across the entire Pareto front.

Since SINR can measure the quality of received signals at users, different communication quality requirements can be met by adjusting the SINR threshold to obtain satisfactory solution sets. Conducting experiments identical to those shown in [Figure 4: see original paper] for different SINR thresholds (4dB, 8dB, 12dB, and 16dB), we plot the median throughput for each power consumption efficiency level in [Figure 5: see original paper].

From the optimal solution sets obtained under different SINR thresholds in the figure above, we can see that as SINR increases, network throughput also improves, but the improvement magnitude is relatively small for the entire network. This is because network throughput depends on the data rates of individual users in the network. According to Shannon' s formula 错误! 未找到引用源。, as SINR continues to increase, the growth trend of data rate slows significantly. Therefore, for small-scale networks, increasing the SINR threshold does not substantially improve overall network throughput. However, for individual users, higher SINR significantly improves their communication quality to meet complex transmission requirements. Additionally, we note that as SINR increases, the number of solutions in the high power consumption efficiency portion of the Pareto front gradually decreases, becoming particularly evident when SINR increases to 16dB. Conversely, the number of solutions in the low power consumption efficiency portion gradually increases. On one hand, when power consumption efficiency is high, transmitters in the network operate at low power overall. Although co-channel interference to the network is small, the low transmission power makes it difficult for some users to meet the corresponding SINR requirements. On the other hand, low power consumption efficiency indicates that the network' s overall transmission power is high, resulting in severe co-channel interference and relatively fewer satisfactory solutions. However, this also narrows the algorithm' s search space, enabling it to quickly converge to optimal solutions.

4 Conclusion

This paper primarily studied the spectrum allocation and power control problem in cognitive wireless networks, formulated it as a multi-objective optimization model, and used an improved multi-objective optimization algorithm to optimize the network, maximizing both power consumption efficiency and throughput. Simulation results demonstrate that the proposed method performs well in searching for optimal solutions and, compared to traditional single-objective optimization methods, can effectively balance performance among multiple objectives in the network, enabling the system to achieve maximum efficiency.

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Note: Figure translations are in progress. See original paper for figures.