Journal of Electronic Research and Application, 2025, Volume 9, Issue 1
http://ojs.bbwpublisher.com/index.php/JERA
ISSN Online: 2208-3510
ISSN Print: 2208-3502

Optimal Power Control for Energy Harvesting in Green Cognitive Radio Networks

Qiliang Gong*

Finance Office, Lanzhou University of Technology, Lanzhou 730050, China

***Corresponding author:** Qiliang Gong, gql0311@lut.edu.cn

Abstract: The integration of cognitive radio and energy has enhanced the utilization efficiency of the spectrum and promoted the application of green energy. To begin with, this paper presents the architecture of green energy-efficient communication and network models. It incorporates the distributed network model and the heterogeneous two-tier network model into the green cognitive radio power control and channel allocation model. The primary focus of this research lies in energy conservation at the physical layer. To mitigate the interference with primary users and address the peak constraint in secondary user power allocation, the article analyzes the system model of the cognitive radio network and subsequently elaborates on the dynamic throughput maximization allocation algorithm. Eventually, through experimental analysis and verification, the distinctiveness and comprehensiveness of the optimal power control for this subject are illustrated.

Keywords: Cognitive radio; Spectrum; Green; Throughput; Power control

Online publication: February 12, 2025

1. Introduction

In the context of the rapid progression of wireless communication technology, cognitive radio technology has emerged as a prominent research focus within the communication domain, serving as an efficacious solution to relieve the scarcity of wireless spectrum resources. Owing to the spectral dynamism and heterogeneity inherent in cognitive radio networks, green cognitive radio endeavors, on the one hand, to explore green energy-saving algorithms and, on the other hand, aims to curtail the energy consumption of wireless network systems and apparatuses, thereby enhancing spectrum utilization and energy efficiency to fulfill the objective of green energy-efficient communication. Presently, energy harvesting in wireless systems has ascended to the forefront as the prime alternative for buttressing "green communication." This approach diverges from traditional battery-powered systems, as its energy supply manifests as an intermittent and sporadic process that varies over time. The modeling paradigm of this system is predicated on the epoch sequence method.

As the system complexity escalates, the advantages become more pronounced. Recursive or iterative methodologies are frequently employed to address target problems. Nevertheless, only a local optimum can be attained, and the attainment of a global optimum cannot be assured. Recently, researchers have been dedicated to investigating data transmission within this system. In this paper, the problem is transmuted into an equivalent quasi-convex analytical formulation to procure an optimal resolution strategy. In previous literature, resource allocation is executed to minimize power consumption while satisfying the Bit Error Rate (BER) criterion [1]. Another literature contemplates energy dissipation in sensing, reporting, and channel switching and proposes a green energy-efficient multi-channel cooperative sensing scheduling framework, which can procure the maximal idle spectrum gain in global false alarm and detection scenarios [2]. One more piece of literature scrutinizes the downlink power control issue of heterogeneous two-tier network nodes [3]. The network architecture encompasses a macro base station node (evolved-NodeB, eNB) and multiple micro-cell home base station nodes (Home evolved-NodeB, HeNB) that collaborate and coexist to attain enhanced Quality of Service (QoS). The Signal-to-Interference-plus-Noise Ratio (SINR) is designated as the performance metric, and the power control of HeNB is transmogrified into a multi-constraint optimization problem to maximize energy efficiency and throughput.

2. System model

2.1. Introduction to radio energy harvesting modes

In this paper, Cognitive Radio (CR) is regarded as an energy harvesting process within a fading channel, and the optimization issue concerning the maximization of throughput is expounded [4]. It is postulated that the processing unfolds as a discrete-time process. Let $Li > 0$, $ai > 0$, $\forall$ i, commencing from the onset of the -th epoch, is designated to signify the harvested energy, which is manifested as $Ein(i) > 0$. The radio spectrum, being an exploitable spectrum, exhibits the trait of low spectrum utilization efficiency. It is capable of accommodating the operational idiosyncrasies of radio in real-time circumstances, endowing it with the attributes of flexibility, effectiveness, and reliability. This technology is competent in discerning the reliable spectrum that is underutilized by the Primary User (PU) and delineates the modality through which the Cognitive User (SU) can proficiently capitalize on this spectrum, thereby electing the efficacious sharing modality between PU and SU [5].

2.2. Construction of the green energy management system model

The green energy management system proffered in this paper hinges on the premise of the optimal power management strategy, wherein the transmit power of each epoch remains invariant. Consequently, is employed herein to denote the transmit power of epoch, to maximize the cumulative throughput of epochs of SU within the time limit. The energy harvested contemporaneously cannot be availed by the preceding epoch. Nevertheless, it can be harnessed by the succeeding epoch as the energy becomes accessible. As the initial stride in the research on CR and energy harvesting, symbolizes the battery capacity, it is hypothesized that the initial value of Emax is 0.

Therefore, the optimization problem of the coexistence regime of energy harvesting and CR within the fading channel can be articulated by **Equation (1)** to **Equation (5)**.

Max{si}Ki= 1 ∑Ki= 1L1/2log(1+aisi) 0 ≤ si (1)

Subject to: ∑li=1 LiSi ≤ ∑li=1 LiSin(K), (2)

For l = 1, ..., K,

Max{si}Ki=1 ∑Ki=1wilog(1+aisi)   0≤si (3)

Subject to: ∑li=1 Lisi≤ ∑li=1LiSin(i) (4)

$w_i \leq L_i/2$, $a_i \leq a_i/L_i$, $s_i \leq L_i s_i$ and $p_i \leq L_i p_i$ (5)

This model adheres to the optimal conditions of the Karush-Kuhn-Tucker (KKT), viz., the green energy-saving criterion. Moreover, the variables are ascertained. Owing to the intricacy of the coexistence regime of energy harvesting and CR, an exact resolution has not been procured in the extant literature. The problem under investigation in this paper can be resolved precisely through circumscribed computations.

3. Power control algorithm optimized based on improved PSO

The crux of this section lies in the realization of a power control algorithm optimized via Particle Swarm Optimization (PSO) [6]. To commence, an inertia weight alteration factor is incorporated to strike a balance between the global and local search capabilities of the PSO algorithm. Specifically, the linearly decreasing weight PSO algorithm, the adaptive weight PSO algorithm, and the enhanced non-linearly decreasing weight PSO algorithm are successively expounded. Subsequently, in the domain of power control, with the distributed cognitive radio network serving as the research framework and under the Underlay mode scenario, the minimum transmission power of cognitive users is derived through the interference temperature model, while ensuring the quality of service for both primary and cognitive users. Moreover, predicated on this model, when cognitive radio apparatuses are engaged in emergency communication scenarios, in conjunction with the concept of the energy detection model, energy constraints are imposed on cognitive users to actualize power control for green energy detection [7].

3.1. Green CR power control model

Power control pertains to the modulation of equipment output power in accordance with specific circumstances, thereby ensuring that the signal transmission power adheres to the requisite standards within the permissible limited range [8]. In light of diverse mathematical theories and constraints, the implementation of CR power control algorithms predominantly encompasses those founded on game theory, cooperative allocation technology, and swarm intelligence optimization.

In the first instance, within algorithms predicated on game theory, game theory is principally categorized into non-cooperative and cooperative game categories. The former is chiefly concerned with handling the competitive comportments of participants, whilst the latter is dedicated to managing their cooperative actions. Through pertinent game strategies, the maximal benefit-seeking behaviors of each player, in the pursuit of maximizing utility functions or minimizing cost functions, are attained. Secondly, in algorithms based on cooperative allocation technology, the latter implies that the functionality engendered by the collaboration of multiple singular networks or technologies far surpasses the aggregate of their individual capabilities. By introducing cooperative allocation technology, the signal service coverage is extended, and the overall performance of the entire system is augmented without necessitating an increment in transmission power. Finally, in swarm intelligence optimization algorithms, which represent a genre of heuristic search optimization algorithms, grounded in certain natural laws and probability conversion precepts, parallel searches are conducted within the solution space to procure the global optimal solution for optimization problems. Typical swarm intelligence optimization algorithms such as genetic algorithm, particle swarm optimization algorithm, ant colony algorithm, and artificial fish swarm algorithm all possess salient attributes like parallelism, adaptability, randomness, and robustness, rendering them efficacious in resolving complex optimization conundrums.

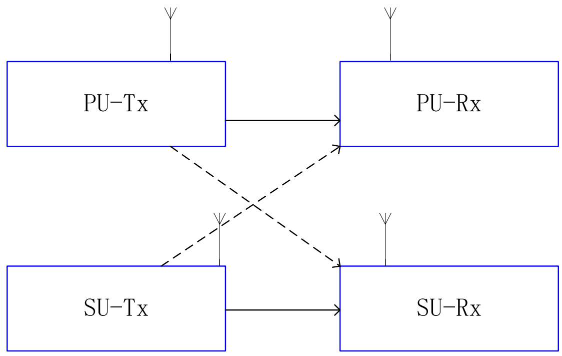

Figure 1. Single carrier single antenna cognitive wireless system model

3.2. CR channel allocation model

In the context of channel allocation models, available spectrum models, game theory models, auction bidding models, and graph theory models are among the prominent ones. Under the aegis of the available spectrum model, interference temperature models and "0, 1" models exist, with the channel allocation based on the interference temperature model being intertwined with the Underlay mode scenario. In a previous study predicated on the shared spectrum access modality, corresponding spectrum allocation algorithms are proffered from both the Overlay and Underlay perspectives [9]. The experimental outcomes disclose that although the spectrum sharing underpinned by Underlay is circumscribed by the PU interference threshold, its environmental requisites are substantially more exacting than those of the Overlay spectrum-sharing approach. Nevertheless, it procures enhancements in user utility and spectrum utilization at the expense of augmented system complexity.

4. Power control algorithm optimized based on improved PSO

4.1. PSO algorithm and improved model

In the process of resolving complex optimization problems, the fundamental PSO algorithm exhibits a susceptibility to becoming entrapped in local optima. To circumvent such a predicament, this study incorporates an inertia weight modification factor with the objective of equilibrating the global and local search capabilities of the PSO algorithm. Concerning the identical test function, the linearly decreasing weight PSO algorithm, the PSO algorithm with adaptive weighting, and the enhanced non-linearly decreasing weight PSO algorithm are successively introduced. Subsequently, their convergence velocities and convergence characteristics are meticulously scrutinized.

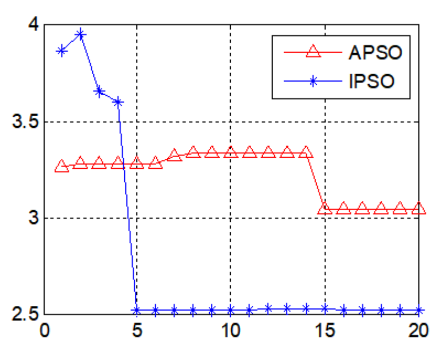

Figure 2. Two algorithms recognize the total transmit power of the user (note: APSO = Adaptive Particle Swarm Optimization, IPSO = Improved Particle Swarm Optimization)

As illustrated in **Figure 2**, under the precondition of ensuring the seamless communication of both the PU link and the SU link, the transmitter within the cognitive link under the IPSO algorithm sustains a diminished transmission power during communication and attains convergence at a more expeditious rate.

4.2. Optimal power control methodology for green energy detection

The amalgamation of Cognitive Radio (CR) and energy detection engenders an augmentation in spectrum efficiency and the exploitation of green energy. The more intricate the system configuration, the more pronounced this advantage becomes. The simplistic geometric interpretation of water-filling is frequently harnessed to address the target problem via recursive or iterative means. The concept proffered in previous literature entails the utilization of the energy detection model to regulate the transmission power of users [10]. The optimized power allocation attributes are construed as a water-filling schema, thereby maximizing the aggregate throughput over the entire temporal span.

In light of this, the present paper applies the energy detection model to CR emergency communication. On the premise of guaranteeing the normal communication functionality of both the PU and the SU, an energy limitation is imposed on the transmission power of the SU, as shown in **Figure 3**.

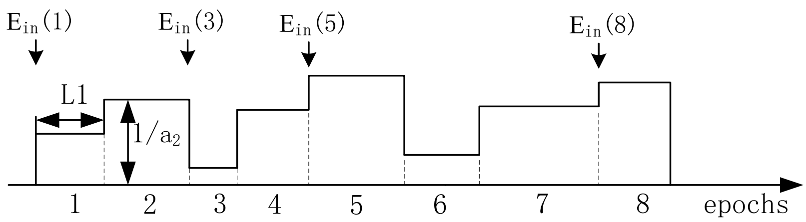

Figure 3. Energy detection model

This measure is enacted to minimize the transmission power and thereby fulfill the objective of green and energy-efficient communication. It depicts the variation in fading gain or the alteration in detected energy. Let Li and a_i respectively denote the duration and the gain of the fading channel within the i-th time interval, where i = 1, ..., K. The transmission power within the i-th time interval is represented by pi, and the energy detected in the *i*-th time interval is denoted by E(i). In accordance with general assumptions, Li > 0, ai > 0, pi > 0, E(i) > 0.

4.3. Simulation experiments and result analysis

This research postulates the existence of one PU link and three SU links within the Cognitive Radio Network (CRN), namely M = 1 and N = 3. The Adaptive PSO (APSO) algorithm and the IPSO algorithm are subjected to comparative analysis using Matlab simulation software, to derive experimental inferences, as shown in **Figure 4**.

As can be discerned from **Figure 4**, in the context of different Secondary Users (SUs) corresponding to disparate Signal-to-Interference-plus-Noise Ratio (SINR) constraint conditions, during the emergency communication procedure, the positional uncertainty of SUs prevails. They might be in close proximity to or at a significant distance from the cognitive base station. Consequently, substantial disparities emerge in the SINR values requisite for ensuring the normal communication of individual SUs. Both the Adaptive Particle Swarm Optimization (APSO) algorithm and the Improved Particle Swarm Optimization (IPSO) algorithm fulfill the minimum SINR constraint prerequisites, thereby guaranteeing the communication quality of SUs.

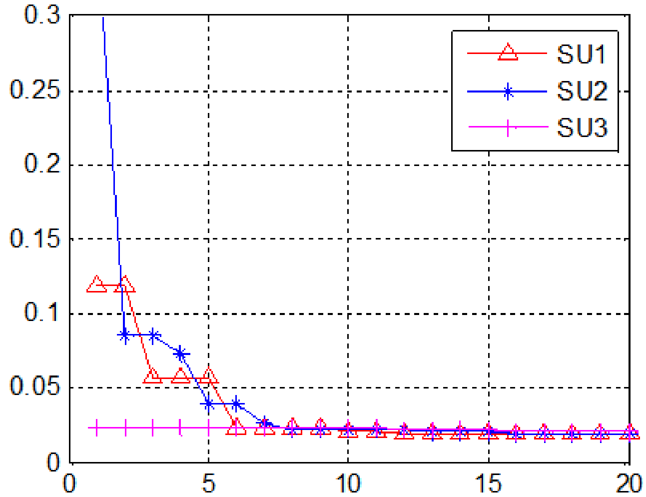

Figure 4. IPSO algorithm and APSO algorithm for Cognitive User Transmitting Power

5. Conclusion

In recent years, the exponential growth of wireless networks and the concomitant diversification of service offerings have been witnessed. Specifically, wireless services predicated on the Internet Protocol, such as voice and video services, have experienced a continuous upsurge. These services exhibit a high degree of sensitivity to network transmission latency and necessitate the satisfaction of specific latency Quality of Service (QoS) requirements. To remediate the aforementioned issues, this study proposes green communication technologies. Green Cognitive Radio (CR) represents a technological paradigm dedicated to the attainment of green communication.

This paper initially undertakes a comprehensive exploration of relevant technical research in the domain of Cognitive Radio. This encompasses the green energy-efficient communication architecture of Cognitive Radio and associated network topologies. Subsequently, the power control model of green Cognitive Radio and the power allocation model based on the utility function are expounded. The latter includes the power control interference model, the resolution of the game theory model, and the green cognitive energy efficiency model. Additionally, a detailed description of the optimal power allocation model is furnished, accompanied by an in-depth analysis of the power control within the effective capacity model, the power control interference temperature model, and the channel allocation in the Cognitive Radio system using integer linear programming. Network modeling is also elaborated upon, incorporating integer linear programming channel allocation, channel allocation for achievable transmission rates, model construction, channel selection strategies, allocation of overlapping channels, static channel allocation, and partial overlapping channel multicast channel allocation. Finally, the basic Particle Swarm Optimization (PSO) algorithm is presented.

Disclosure statement

The author declares no conflict of interest.

References

[1] Flischione C, Johansson KH, Sangiovanni VA, et al., 2009, Minimum Energy Coding in CDMA Wireless Sensor Networks. IEEE Transactions on Wireless Communications, 8(2): 985–994.

[2] Haenggi M, Ganti RK, 2009, Interference in Large Wireless Networks. Foundations & Trends in Networking, 3(2):127–248.

[3] Clancy TC, 2007, Formalizing the Interference Temperature Model. Wireless Communications & Mobile Computing, 7(9): 1077–1086.

[4] Jha V, Tripathi P, 2025, Selective Hypothesis Testing in Cognitive IoT Sensor Network. Journal of Supercomputing, 81(1): 133.

[5] Wang L, Lam KY, Zhang JX, et al., 2024, Spectrum Optimization in Cognitive Satellite Networks with Graph Coloring Method. Wireless Networks, 30(5): 3443–3452.

[6] Macit B, Ragi SD, Moseley I, et al., 2024, A Case-Control Study: Epigenetic Age Acceleration in Psoriasis. Archives of Dermatological Research, 316(7): 340.

[7] Roy S, Sankaran S, Zeng MN, 2024, Green Intrusion Detection Systems: A Comprehensive Review and Directions. SENSORS, 24(17): 5516.

[8] Swearingen MT, Michael JB, 2024, Resilient Without Zero Trust. COMPUTER, 57(1):120–122.

[9] Boyd S, Vandenberghe L, 2004, Convex Optimization. Cambridge University Press, UK.

[10] Andrews JG, Claussen H, 2012, SUs: Past, Present, and Future. IEEE Journal on Selected Areas in Communications, 30(3): 497–508.