Dynamic Spectrum Allocation Mechanism of Joint Power Control and Channel Allocation

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Abstract

Aimed at the matter about multiuser spectrum allocation of underwater and limited capacity, this paper proposes the dynamic spectrum mechanism of joint power control and channel allocation. Based on the power distribution algorithm of the minimum of outage probability, the author proposed a dynamic spectrum allocation algorithm that combined joint power with channel allocation (JCCA) to maximize the capacity of the underwater acoustic channel. To address these issues about multiuser interference in decoding receiver, this algorithm makes the spectrum allocation optimally when accessing to the authorized spectrum which is limited and maximizing utility function. Simulation results show that the algorithm can save energy. Realize a better multiuser spectrum allocation and increase system capacity when it combines with JPRCPC.

Keywords: Multiuser spectrum allocation, Joint power, Channel allocation, Dynamic spectrum allocation

1 Introduction

Underwater Sensor Network (USN) refers to the deployment of underwater sensor nodes with low energy consumption and a certain communication distance to the designated sea area, and the automatic establishment of the network based on self-organizing ability of the nodes. Sensors are used by nodes in the network to monitor and collect all kinds of monitoring information in the distribution area of the network in real-time [1]. The real-time monitoring information will be sent to the surface base station and finally to the user through underwater nodes with long-distance transmission capacity after data fusion and other information processing. Underwater sensor networks are widely used in underwater resource exploration, marine geographic data collection, earthquake and tsunami warning, national defense and security, etc. However, the underwater acoustic channel is one of the most complex channels so far. The transmission speed of the underwater acoustic wave is 1500 m/s, which is five energy levels lower than the propagation speed of wireless electromagnetic waves on land [2]. Therefore, the signal fading is relatively slow, and the cumulative interference at the receiver is more serious than before. It is difficult for the transmitter to obtain the channel state information feedback by the receiver, and it is hard to effectively adjust the sending power to compensate for the fading channel, resulting in a high probability of interruption, low network capacity, and large energy consumption loss.

The coding technology can effectively reduce the waiting time of packets, so it is suitable for the underwater acoustic modem according to the underwater acoustic channel [3]. The block encoding system buffers a block containing M packets at the transmitter and encodes them into a larger set of N(N≥M) packets for sending [4]. At the receiver, the original packet containing information can be recovered from any of M or more packets in the subset received. The concept of a packet coding network was first proposed in [5]. Compared with the traditional network, packet coding improves the overall throughput efficiency.

In [6-10], stochastic linear block coding for underwater acoustic communication is studied. In an underwater acoustic network, rateless coding is used to realize reliable file transmission in [6], and a feedback link is used to inform the transmitter when to stop sending coded packets. Because of the low frequency of feedback compared with traditional ARQ technology, the overall system performance is improved. The optimal broadcasting strategy of underwater acoustic networks based on random linear block coding is studied in [7], and the performance is improved compared with traditional ARQ technology. The optimal scheduling problem of random linear block codes in semi-duplex links is studied in [8], and the optimal number of block codes is given to

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minimize the average time required to complete a packet block transmission. Random linear block coding without feedback link is introduced in [9] to determine the number of coding groups to be transmitted, enabling the receiver to decode the original group with pre-specified reliability. For the channel with severe fading, [11] considered the optimization of packet-level and bit-level coding, and improved the performance by adding redundancy to erase and correct the coding of packets. In [12], the joint optimization problem of average throughput and packet loss rate in the network coding system is considered. The results show that the non-feedback packet coding method has better performance in average throughput and packet loss rate. In [13], joint power and rate control of block fading channels are studied. The authors define utility functions and cost functions to specify an optimization framework that aims to maximize transmission rates while minimizing power consumption. In [13], Milica Stojanovic proposed joint force and speed control packet encoding on fading channel (JPRCPC) for digitally encoded packet transmission determined to achieve predetermined downtime/reliability criteria. The experimental results show that the system has a significant effect on energy saving and throughput efficiency. In narrow band, multipacket coding and slow fading lead to the accumulation of decoders. A joint power and channel allocation method for fading channel dynamic spectrum access is proposed. For narrowband cumulative jamming, JPCAPC achieves the optimal channel allocation under the limit of stop probability.

2 System Model

In each loop, each original data M at the transmitter is encoded into a set of packets N(N < M), as shown in Figure 1, h_i is the channel gain of Rayleigh channel from the transmitter to the receiver, and it obeys an exponential distribution with a mean of 1, called $h_i \sim \exp(1)$. The transmitter sends the data packet at the same frequency in a supposed certain time T, only the data packet sent to transmitter TX0 is a useful signal for the receiver RX0, while other data packets sent to transmitter TXi are all interference to the packets sent to TX0. a is the path attenuation factor, d_i is the transmission distance of data packets from the transmitter to receiver RX0, and the cumulative interference is represented as:

$$I_i = \sum_{i \in \Pi(\lambda)} h_i d_i^{-a} \quad \textbf{(1)}$$

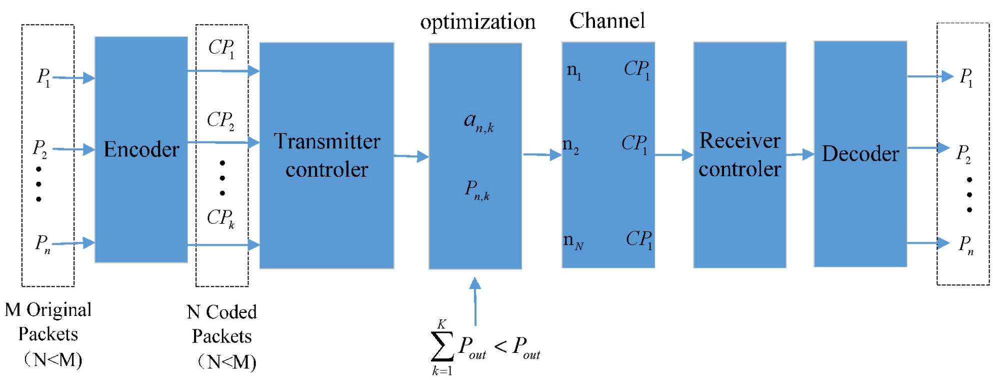

Figure 1. System model

Cumulative interference increases the probability of interruption, and the probability of transmission capacity is proposed by Weber et al. If the probability of interruption is limited, which defined as the product of the maximum space transmission density per unit area, successful transmission probability, and transmission rate, the expression shall be:

$$C(\lambda) = R\lambda(1-\eta) \quad \textbf{(2)}$$

R is the transmission rate of each data packet, λ is the number of transmitted packets, η is the probability of interruption, λ^{η} is the maximum number of packets allowed to be sent under the premise of limited interrupt probability.

Transmission capacity represents the spectrum utilization in a unit area of a unified network. The more packets sent per unit area, the more network data flow per unit time, and the larger corresponding transmission capacity. However, increasing the number of packets sent blindly also means the probability of interference between packets within the network is higher, which lead to higher interrupt probability and lower transmission capacity. Therefore, the definition of transmission capacity reflects the mutual restriction between the capacity and quality of the communication system, which can be used as a performance index.

3 Dynamic Spectrum Allocation Mechanism of Joint Power and Channel Allocation

The dynamic spectrum allocation mechanism is one of the research hotspots of cognitive radio technology, and it finds and uses the available spectrum efficiently to meet the needs of cognitive users. Dynamic spectrum allocation mechanism can improve the efficiency of spectrum resource utilization greatly by opportunity access to the authorized spectrum. The expression of the optimization is shown as:

$$a = argmax\, U(a \mid a \in A, \xi = \xi_1) \quad \textbf{(3)}$$

Where A is a collection of various algorithms and parameters that can be used in the dynamic spectrum sharing system. U() is a utility function, which can be either the maximization of capacity or the maximization of spectral efficiency, etc. ξ is the spectrum usage behavior of the current authorization system, which represents its spectrum using constraint to the unauthorized system. That is to say, in the research of dynamic spectrum access technology, the influence of the behavior of the authorization system on its working environment must be considered.

The mechanism of joint power control and channel allocation is proposed to solve the problem of scarce available spectrum resources of underwater effectively and a high probability of interruption of packet interference. The flow chart is shown in Figure 2.

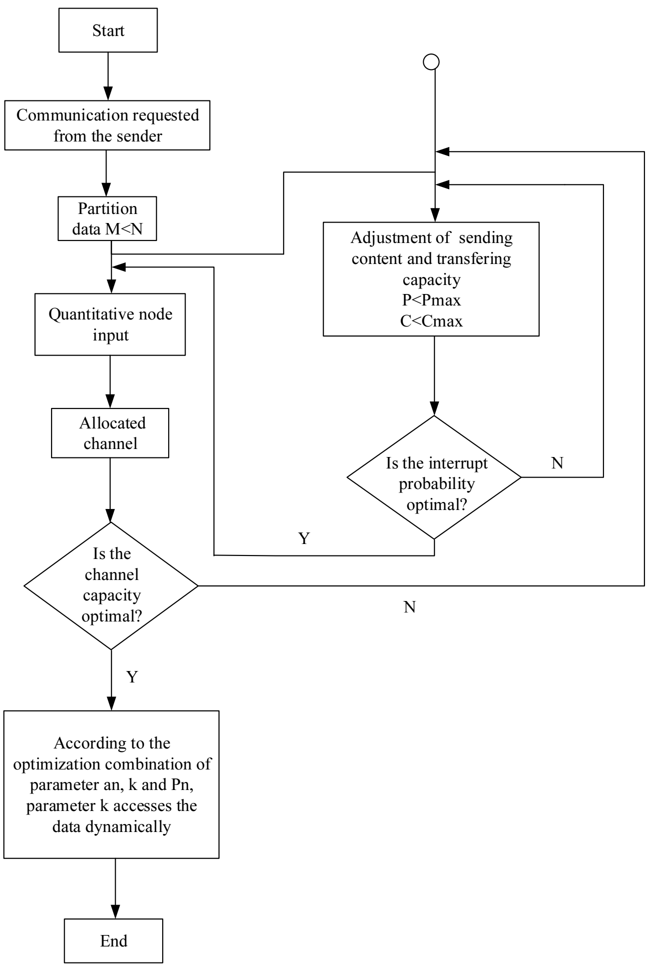

Figure 2. Algorithm of JCCA flow chart

3.1 Algorithm of Power Control

The underwater acoustic channel is one of the most complicated channels in the world, which has the characteristics of time-space-frequency variation, narrow bandwidth, and serious doppler shift.

Sending data with maximum power, the Laplace transform of the interference is:

$$H(f,t) = \Sigma_n h_n(t_n)\gamma_n(f,t)e^{-j2\pi f \tau_n(t)}, \quad \textbf{(4)}$$

where $\gamma_n(f,t)$ is scattered noise, $\tau_n(t)$ is doppler shift.

Transmit packets with maximum transmit power

$$SINR = \frac{p00^{-\alpha}{}_{\max}}{\sum_{i\in\pi(\lambda)}^{\Sigma} p00_i^{-\alpha}{}_{0\max}} \quad \textbf{(5)}$$

According to [14], the cumulative interference is

$$\Sigma\, I_i(s) = \exp\{-\lambda\pi E[H^\delta]\Gamma(1-\delta)s^\delta\} \quad \textbf{(6)}$$

According to the above properties, when data sent with a maximum power, we can obtain

$$P^t{}_{out} = 1 - e^{-\lambda\pi d^2\beta^\delta E[H^\delta]E[H^{-\delta}]} \quad \textbf{(7)}$$

We define $P^t{}_{out}$ as outage probability. Now consider network transmission capacity with constrained outage probability.

$$C = R\lambda^{Pout}(1-P_{out}) \quad \textbf{(8)}$$

Transmit packets with $P_t \prec P_{\max}$, we obtain

$$\Sigma\, I_i^t(s) = \exp\{-\lambda\pi E[H^\delta]\Gamma(1-t\delta)s^{t\delta}\} \quad \textbf{(9)}$$

Adjusting transmission power,

$$P^t{}_{out} = 1 - e^{-\lambda\pi d^2\beta^\delta E[H^{-t\delta}]E[H^{-1+t\delta}]} \quad \textbf{(10)}$$

$$C = R^{P^t out}(1-P^t{}_{out}) \quad \textbf{(11)}$$

From (11), $\Sigma\, I_i^t(s)$ is the accumulated interference of channel fading. It can be verified that outage probability outage $P^t{}_{out}$ decreased with power control exponent since transmission power is adjusted. The results show that transmission power is adjusted at (10), and the outage probability has a minimum value.

3.2 Channel Allocation Algorithm

In this section, we consider a channel allocation algorithm that sends data with a suboptimal power to make a deduction of the formula of transmission capacity and then allocating channels on the basis of the number of nodes. Finally, optimal outage probability and network transmission capacity were obtained by the channel allocation algorithm.

Within the communication coverage area, multiple user interference increased with density, and mobility of nodes and then the information may not be decoded properly in the target node, while outage probability increased significantly. The channel bandwidth is divided into n sub-channels.

According to Shannon Theorem, the channel capacity of user K is

$$C_k = \sum_{n=1}^{N}(1-P_{out})a_{k,n}B_n \log_2(1+\frac{P_{k,n}\,|\,h_{k,n}\,|^2}{N_0 B_n a_{k,n}}) \quad \textbf{(12)}$$

Where B_n is the bandwidth of sub-channel, P_{out} is the outage probability of Channel n is selected by user k, N_0 is noise power, $a_{k,n}$ is the channel allocation matrix. When $a_{k,n}=1$, it means that channel n is selected by user k for communication. Conversely, $a_{k,n}=0$ means that channel n is not selected by user k for communication.

The channel capacity of cognitive Underwater Sensor Network is

$$C_k = \sum_{n=1}^{N}\sum_{k=1}^{K}(1-P_{out})a_{k,n}B \log_2(1+\frac{P_{k,n}\,|\,h_{k,n}\,|^2}{N_0 B_n a_{k,n}}) \quad \textbf{(13)}$$

The joint power control method is based on the objective of optimizing channel capacity, and the optimization problem of network capacity maximization is

$$C = \sum_{n=1}^{N}\sum_{k=1}^{K}(1-P_{out})a_{k,n}B \log_2(1+\frac{P_{k,n}\,|\,h_{k,n}\,|^2}{N_0 B_n a_{k,n}}) \quad \textbf{(14)}$$

$$\begin{aligned} s.t.\quad & C_1 \quad \sum_{k=1}^{K} P_{k,n} < P_{\max} \\ & C_2 \quad \sum_{k=1}^{K} P_{out} < P_{out} \\ & C_3 \quad a_{n,k} \in \{0,1\} \end{aligned}$$

Where $P_{\max}$ is maximum transmission power.

The Lagrange multiplier method for the above optimization problem is

$$\begin{aligned} L(P_{n,k}, a_{n,k}) &= \sum_{k=1}^{K}\sum_{n=1}^{N}(1-P_{out})B \log_2(1+\frac{P_{k,n}, h_{k,n}}{N_0 B}) \\ & \lambda_k(\sum_{n=1}^{N} P_{k,n} - P_k) + \beta_n(\sum_{k=1}^{K} a_{k,n} - 1) \end{aligned} \quad \textbf{(15)}$$

Then, KKT is:

$$\frac{\partial L(P_{k,n}, a_{k,n})}{\partial P_{k,n}} = 0 \quad \textbf{(16)}$$

$$\frac{\partial L(P_{k,n}, a_{k,n})}{\partial a_{k,n}} = 0 \quad \textbf{(17)}$$

$$\lambda_k(\sum_{n=1}^{N} P_{k,n} - P_k) = 0 \quad \textbf{(18)}$$

$$\beta_n(\sum_{k=1}^{K} a_{k,n} - 1) = 0 \quad \textbf{(19)}$$

Taking the derivative on (15)

$$\frac{\partial L(P_{k,n}, a_{k,n})}{\partial P_{k,n}} = 0 \Rightarrow P_{k,n} = \begin{cases} \dfrac{-1}{\lambda_k} - \dfrac{N_0 B}{h_{k,n}}, & a_{k,n} = 1 \\ 0 & , a_{k,n} \end{cases} \quad \textbf{(20)}$$

$$\frac{\partial L(P_{k,n}, a_{k,n})}{\partial P_{k,n}} = 0 \Rightarrow \ln(\frac{(P_{k,n}, h_{k,n})}{\partial_{k,n}}) - \frac{P_{k,n}, h_{k,n}}{a_{k,n}} = \beta_n \quad \textbf{(21)}$$

$$a_{n,k} = argmax(\frac{h_{n,k}}{\lambda_k}) \quad \textbf{(22)}$$

$$\lambda_k = \frac{N_k}{P_k + \sum_{n=1}^{N_k} \dfrac{N_0 B}{h_{k,n}}} \quad \textbf{(23)}$$

Where, $a_{n,k}$ and λ_k' are Optimum coefficient.

4 Simulation and Results

Here, we present some numerical results to evaluate the performance of our proposed PCCA strategies. We compared the outage performance of the proposed strategies with that of JPRCPC. Assume the simulation area is 2000m *2000m, the numbers of nodes vary from 0 to 160. The simulation parameters are shown in Table 1.

Table 1. Simulation Parameter Setting

Simulation Area	2000m*2000m
Number of Node	0-160
Transmission Distance	1m-300m
Channel Bandwidth	5-20kHz
Signal-to-Noise Ratio	15-30dB
Doppler Frequency Shift	100-300Hz

In Figure 3, we present the relationship between outage probability and power control exponent. Figure 3 is for the case of path loss exponents, where three different values of a, ie., $a=3$, $a=4$, and $a=5$ are assumed. Different parameters represent the different environments for wireless channels. As shown, the PCCA is more effective and achieves the minimization of the outage probability. This simulation is provided to demonstrate the effectiveness of the proposed power control strategies.

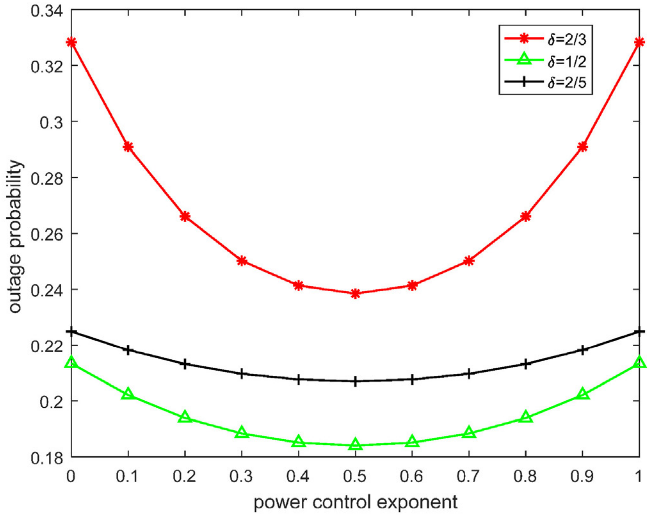

Figure 3. Power control exponents w vs. outage probability

In Figure 4, we can see that outage probability increased with the density of nodes. As shown, the PCCA strategy achieves the minimization of the outage probability. In the case of the same density, the outage probability of PCCA and JPRCPC are respective 0.55 and 0.76. The outage probability is significantly decreased by the PCCA compared with that of the JPRCPC, which decreased by 23%.

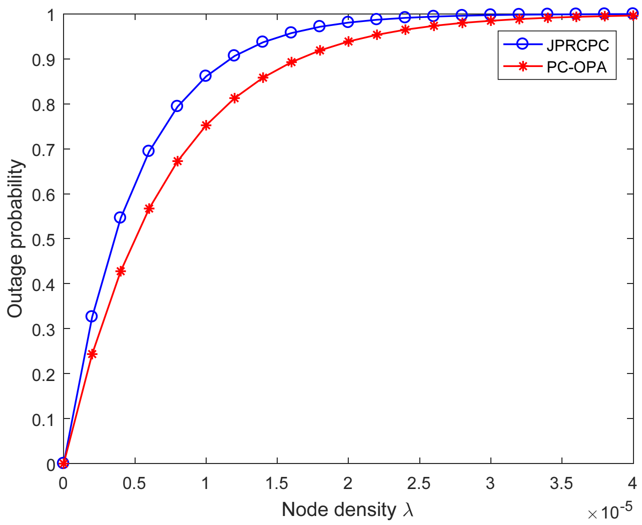

Figure 4. Outage probability for different algorithm vs. λ density of nodes

In Figure 5, we plot the outage probability as a function of the distance from 0 to 250 m. The outage probability varies with the distances. It should be noted that the expression in (7) is for the case of channel fading. The method of PCCA provides channel fading variations for a different distance and adaptively adjusts the transmission power according to the time-varying characteristic of wireless channels, thus the outage probability of PCCA is lower compared to JPRCPC.

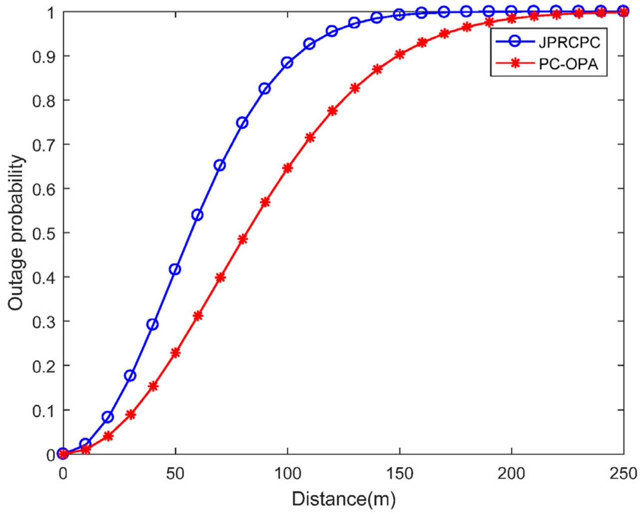

Figure 5. Outage probabilities vs. distance

Figure 6 shows that the throughput is varying as the node densities. With the increase of the density nodes, the throughput grows more. The PCCA achieves the most throughputs among the three algorithms. In the case of the same density of nodes, the network throughput of PCCA was significantly higher than that of JPRCPC, and then the successful delivery rate of PCCA is 600. The high delivery rate makes more throughputs but makes more cumulative interference. As shown, the PCCA can adjust the transmitter power according to CSI, in which the aim is to be optimal the outage probability. Therefore, among the three power control algorithm the PC-OPA achieves the optimal outage probability and then achieves the most throughput.

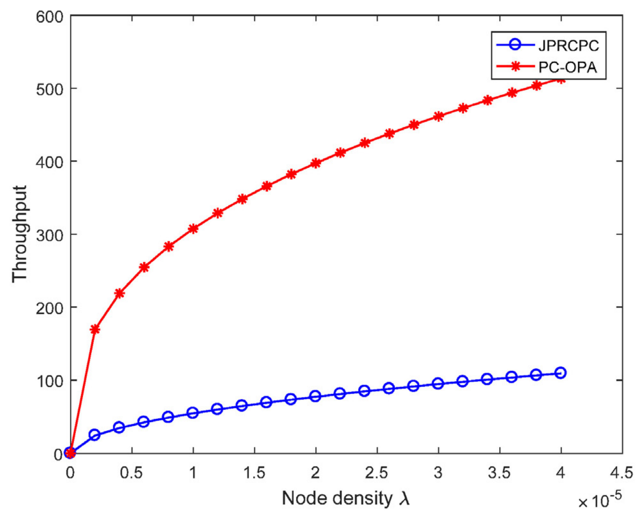

Figure 6. Throughput for different algorithm vs. λ density of nodes

Figure 7 shows the relationship between node density and channel capacity. With the increase of node density, channel capacity increases more. When the node density reaches a fixed value, the channel capacity tends to be saturated. As node density increases, the probability of interruption increases, the number of successful nodes decreases, and the channel capacity decrease. To solve this problem, a dynamic spectrum allocation algorithm for joint power control and channel allocation is proposed. This algorithm takes into account the serious problem of multi-user interference, takes the optimized channel capacity as the target, and adopts the combined power control method to reduce the interruption probability and improve the network capacity. As the node density increases gradually, the channel capacity of the dynamic spectrum allocation algorithm based on joint power and channel allocation is higher than that of the JPRCPC algorithm under the same density.

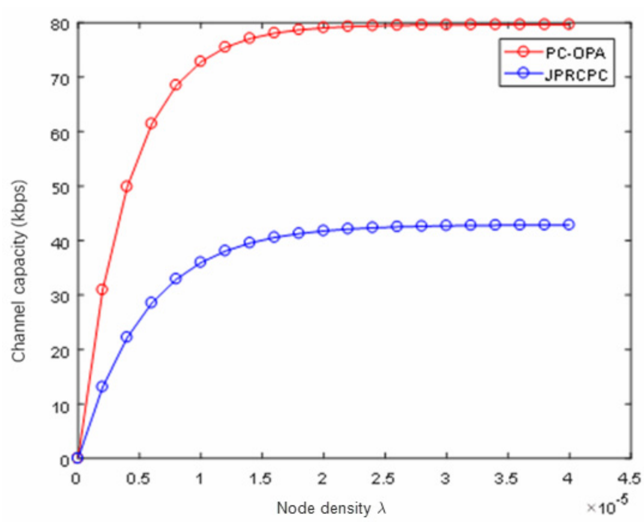

Figure 7. Channel capacity for different algorithm vs. λ density of nodes

Figure 8 shows the relationship between transmission distance and channel capacity. As can be seen from Figure 3, when the distance between the sending node and the receiving node increases, the interrupt probability also increases. This is because when other parameters are fixed, the distance between the sending node and the receiving node increases, the signal power received by the receiving node decreases. That is, the SNR of the receiver decreases, and the interrupt probability also decreases. Figure 6 shows the opposite trend in Figure 3. Channel capacity decreases as the distance between the sending node and receiving node increases. Therefore, when the distance increases, the probability of network interruption increases, and the channel capacity of the network will decrease.

5 Conclusion

In this paper, to address these issues, such as interference in multi-users, high outage probability, and shortage of spectrum resources, we proposed a power control and channel allocation algorithm, called

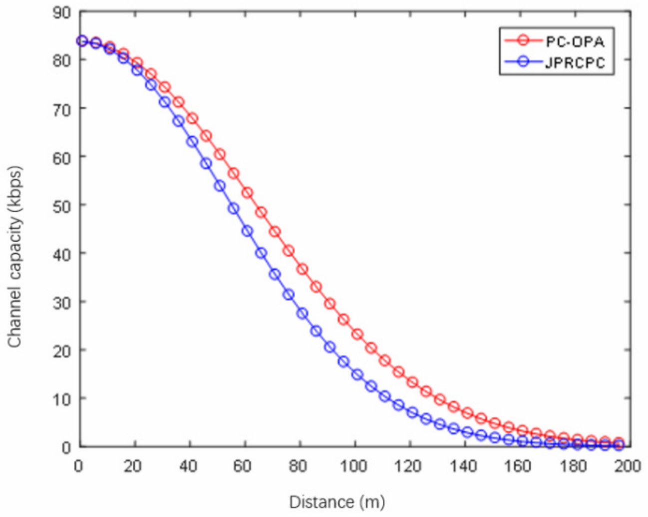

Figure 8. Relationship between transmission distance and channel capacity

simply PCCA. The PCCA analyzes the situation of multiple users' interference through stochastic geometry and then establishes relationship between outage probability and channel accumulated interference. According to the expression, we adjust the transmitter power and are optimal for the outage probability. To fulfill spectrum access, we build the channel allocation model by Lagrange optimization theory and then derive the expression between channel capacity and channel allocation Simulation results are provided to demonstrate the effectiveness of the proposed channel allocation strategies. The simulation results show that the outage probability of the PCCA decreased by 25% and the channel capacity is increased by 40%, compared to JPRCPC.

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