J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 7611--7627

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Study on collaborative spectrum sensing of multi-satellite low orbit satellites based on multi-satellite collaborative beamforming and intelligent algorithms

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ABSTRACT

Low earth orbit satellites can help narrow the digital divide and provide low latency and high-speed Internet connections. However, they are extremely fast and cannot stay over a single place. In addition, during the process of circumnavigating the ground, it can only be exposed to a fixed location for a short period of time. In response to the above issues, a collaborative spectrum sensing algorithm based on fuzzy integration is proposed, and an intelligent algorithm is obtained by combining alliance game algorithm. Finally, a multi-satellite low orbit satellite collaborative spectrum sensing method based on multi-satellite cooperative beamforming and intelligent algorithm is designed. The research results indicated that the correct detection probability of intelligent algorithms was positively correlated with the signal-to-noise ratio. At a signal-to-noise ratio of -11dB, the probability of correct detection reached a steady state of 1. Under strong interference conditions, when the number of participating satellites in the array was 10, the detection probability of the research method approached 1, and the optimal satellite array power utilization rate obtained was 93.4%. The above results indicate that the research method can reduce the impact of strong ground interference signals and fully tap into the spatial resources available for low orbit satellites.

Keywords: Multi-satellite collaboration, Intelligent algorithm, Low Earth orbit satellite, Beamforming, Spectrum sensing

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Received 10 January 2024; Revised 15 February 2024; Accepted 25 December 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-416

1. Introduction

In recent years, with the rapid development of aerospace technology, the scale of space information network has gradually increased, and it plays an increasingly important role in many fields such as national security, military field and transportation management [1-2]. Among them, satellite communication system is gaining popularity day by day because of its unique features such as wide coverage area and large transmission capacity [3]. Satellite communication system is mainly composed of satellites, and the types of satellites are not single, mainly containing low orbit satellites, medium orbit satellites and geosynchronous orbit satellites, this method of dividing the different types of satellites is mainly based on the fact that all satellites are not distributed in the same orbital altitude, and correspondingly, there are three different kinds of satellite network systems [4-7]. Among them, the low orbit (LEO) satellite communication system has been gradually emphasized by the mobile communication researchers of various countries in recent years for its advantages of low delay, small path loss, and low single star cost [8-9].

At present, the development of LEO satellite communication system is more mature in foreign countries, but it is still in a stage of transformation from technology to engineering in China [10-11]. At the same time as the rapid development of satellite communication networks, the volume of communication services has also increased widely, and at the same time the spectrum data in the communication process has also increased dramatically [12]. In this process, reasonable handling of these spectrum data can effectively alleviate the spectrum resource crisis, low-orbit satellites can be collected spectrum data to generate spectrum posture, thus serving as the basis for the construction of spectrum maps, through the integration of some discrete spectrum data, so as to predict the future direction of the development of spectrum posture [13-16]. Spectrum posture can present spectrum data in multiple directions such as air, time, and frequency domains, which are combined with geolocation information system, thus constructing a rich spectrum map. The spectrum map integrates and visualizes the spectrum data, thus providing users with intuitive information about the spectrum state [17-19]. The original purpose of spectrum sensing technology is to solve the problem of "false lack" of spectrum resources, in other words, it is used to find "spectrum holes", so as to achieve the purpose of improving the utilization of spectrum resources. In addition, spectrum sensing technology is also one of the means to realize the security control of spectrum situation [20-22].

2. Multi-satellite low orbit satellite CSS based on MSCB and intelligent algorithms

2.1. CSS algorithm design based on fuzzy integral

A new round of technological revolution and industrial transformation is deepening. The new generation of information and communication technology has become a key driving force for empowering high-quality economic and social development. The importance of radio spectrum and satellite orbit resources is becoming increasingly prominent. However, due to the fading characteristics of wireless communication channels and the long transmission distance, the monitoring performance of frequency equipment for sensing the ground by a single satellite is inaccurate. Therefore, a CSS algorithm based on fuzzy integration is proposed to optimize the effect of multi-satellite cooperative sensing. Fuzzy integration extends the concept of traditional integration to fuzzy sets and fuzzy functions, and can be used as a method for processing fuzzy information collected by nodes to obtain corresponding spectrum sensing results. The fuzzy integral type used in the study is choquet fuzzy integral, which integrates information through fuzzy measures and allows for consideration of the interactions and dependencies between different factors in the decision-making process. Firstly, a system operation model driven by a single frequency user in collaboration with multiple cognitive satellites is constructed, as shown in Figure 1.

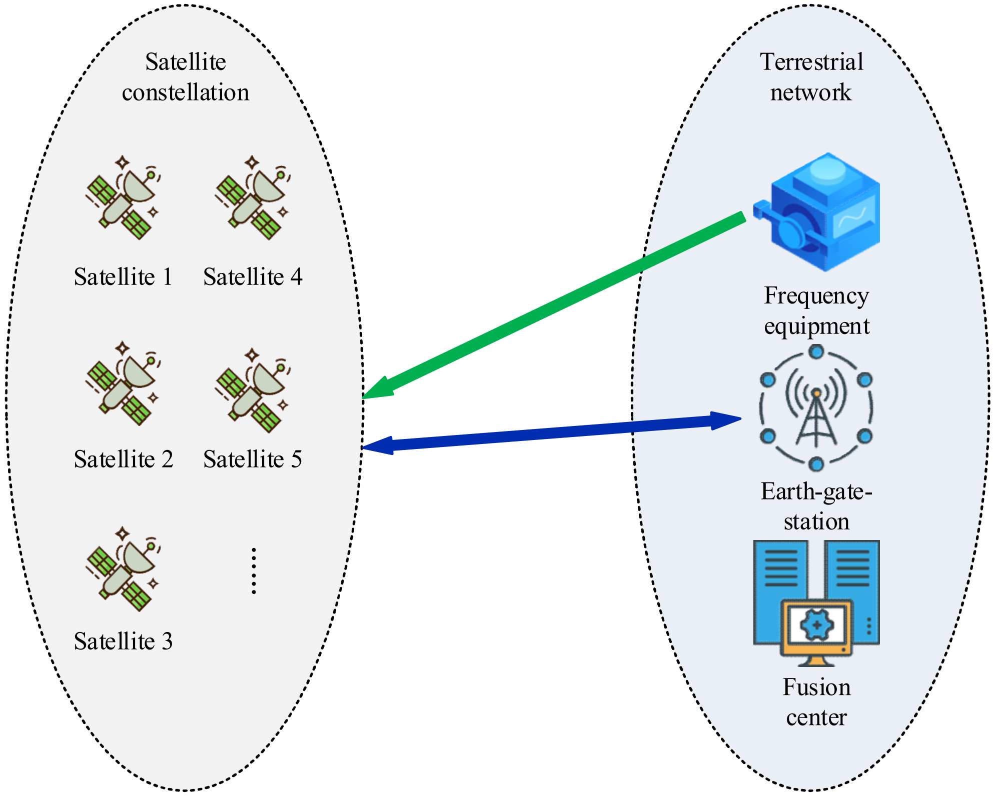


Fig. 1. Schematic diagram of a system operation model driven by a single frequency user in collaboration with multiple cognitive satellites

In Figure 1, the constructed scenario mainly targets a single frequency user who perceives the ground. The spectrum sensing process can be calculated using a binary hypothesis model, as shown in equation (1).

$$s(t) = \begin{cases} g(t), S_0 \\ z \times f(t), S_1 \end{cases} \tag{1}$$

In equation (1), S_0 and S_1 correspond to unoccupied and occupied states, respectively. $s(t)$ and $g(t)$ are the received signal and noise signal during the detection frequency band process, respectively. $f(t)$ and z respectively represent the wireless channel gain and transmission signal between frequency devices during the detection of frequency bands. In the process of spectrum sensing, ζ needs to meet the following conditions, as shown in equation (2).

$$\zeta = T \times W \tag{2}$$

In equation (2), T and W correspond to detection time and bandwidth, respectively. At the same time, assuming that the number of sampling points for the user to obtain the signal is $M = 2\zeta$, the energy detection J received by the cognitive user can be calculated, as shown in equation (3).

$$J = \sum_{m=1}^{M} s^2(g) \tag{3}$$

Thus, the CSS algorithm based on fuzzy integration can be used in the CSS method, and its operating framework is shown in Figure 2.

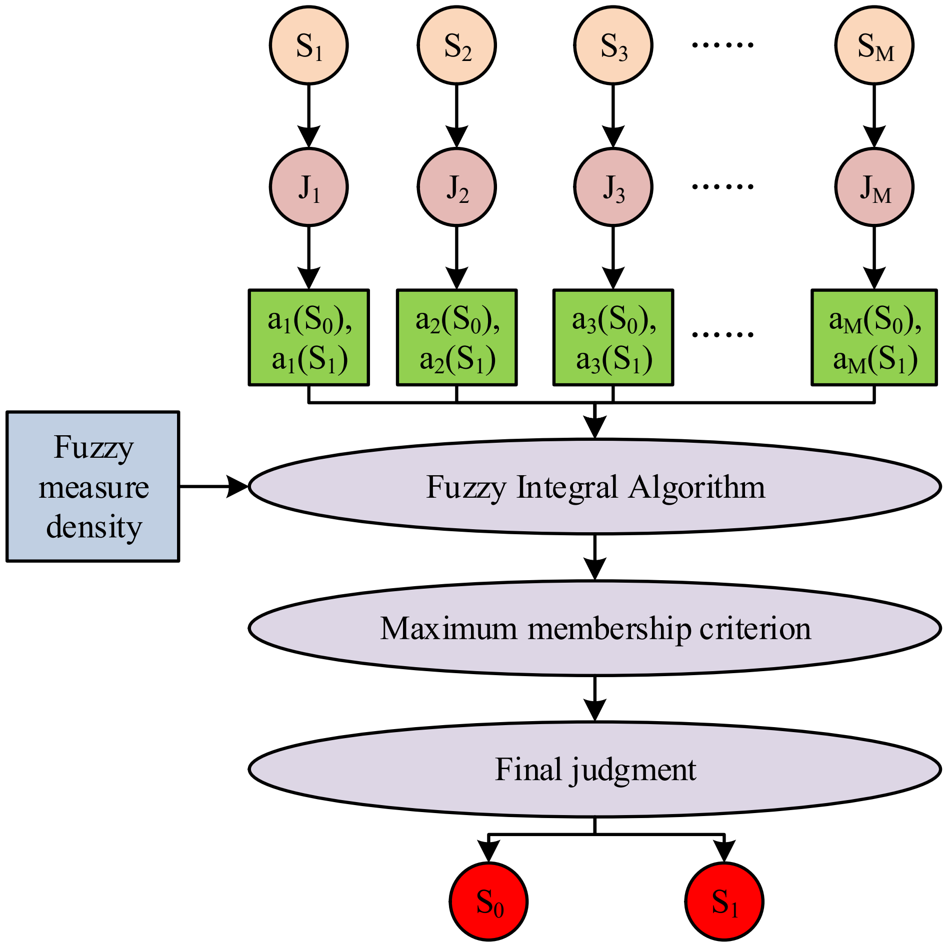


Fig. 2. CSS algorithm running framework based on fuzzy integral

In Figure 2, perception is first achieved through the energy detection method. Two frequency state assumptions are designed to calculate the J value. At the same time, a pair of measurable functions $a_i(S_0)$ and $a_i(S_1)$ are established based on the distribution followed by relevant statistics, representing the membership values S_0 and S_1 obtained by cognitive satellite i based on the J_i -value. Then, the fuzzy measure value v_i is calculated, and the final decision result is obtained through transmission processing and Choquet fuzzy integration. The expression for the fuzzy measure density of a single cognitive satellite is shown in equation (4).

$$\rho_i = \frac{1 - P_x^i + P_t^i}{2} \tag{4}$$

In equation (4), P_x^i and P_t^i correspond to the false alarm probability and correct detection probability of cognitive satellites in the shadow Rayleigh fading channel. By substituting it into equation (5), the fuzzy measure value $v(O_i)$ can be obtained.

$$\begin{cases} v(\{x_i\}) = v_i \\ v(Z_1) = v(\{x_1\}) = v_1 \\ v(Z_i) = v_i + v(Z_{i-1}) + \alpha v_i v(Z_{i-1}), i = 1,2,\ldots,n \end{cases} \tag{5}$$

In equation (5), $X = \{x_1, x_2, \ldots x_i, \ldots, x_n\}$ is a non empty finite set, $v(Z_i)$ represents the importance of Z_i to the final decision, and α represents the interaction parameter. This can be applied to the final judgment results in the future.

2.2. Construction of CSS intelligent algorithm integrating alliance game

The above method is difficult to cope with the limitations of the inter satellite transmission pipeline. Therefore, based on the above method, the CSS intelligent algorithm is obtained by combining it with the AG. The AG algorithm is mainly used to analyze how multiple participants form an alliance through cooperation, thereby achieving the maximization of common interests. At the same time, participants can increase profits through collaboration rather than acting alone, so the core issue is the distribution of collaborative benefits and how to ensure the stability of the alliance. The specific process of applying AG algorithm to collaborative perception of cognitive satellites is as follows. Firstly, assuming there are K cognitive satellites involved in collaborative perception, an alliance is formed. A sub alliance is a set composed of non empty subsets B, whose payoff value is calculated by the utility function $VALUE(B)$. The corresponding sub AG is represented by $(B,VALUE)$. The eigenvalues play a decisive role in the type and form of subsequent games. In the application of cognitive radio technology, this value mainly reflects the relationship between detection probability and false alarm probability, as expressed in equation (6).

$$VALUE(B) = 1 - P_{n,b} - COST(P_{x,b}, \psi) \tag{6}$$

In equation (6), $P_{n,b}$ and $P_{x,b}$ correspond to the missed detection probability and false alarm probability of B, respectively, where n represents the overall alliance structure or overall alliance set. $COST(P_{x,b}, \psi)$ represents the corresponding cost of B. ψ represents the upper limit of $P_{x,b}$. To better control the cost brought by $COST(P_{x,b}, \psi)$, the calculation of this function has been optimized, as shown in equation (7).

$$COST(P_{x,b}, \psi) = \begin{cases} -\psi^2 \ln\left[1 - \left(\dfrac{P_{x,b}}{\psi}\right)\right], P < \psi \\ +\infty, P_{x,b} \geq \psi \end{cases} \tag{7}$$

In equation (7), $COST(P_{x,b}, \psi)$ will increase with the increase of $P_{x,b}$. When it increases to ψ, it will become infinite. The size of the alliance can be further calculated using ψ, as shown in equation (8).

$$N_{\max} = \frac{\ln(1-\psi)}{\ln(1-P_c)} \tag{8}$$

In equation (8), P_c represents the probability of the user making an occupancy decision based on feature information when the frequency device is not occupied in the detected frequency band. Based on the above analysis, the AG can be applied to multi-satellite cooperative spectrum sensing scenarios. To achieve more stable alliance partitioning, comparison rules can be used to compare sub alliances. In this process, the cognitive satellite in the game is set to satisfy $i \in K$, while the sub alliances B_i and B_j are given. If i belongs to B_i and B_j, and $B_i \triangleright B_j$, it indicates that i has a stronger willingness to enter B_i. If in an equal situation, it means that the effect of i joining any sub alliance is the same. In addition, the alliance also follows the merging and splitting rules, that is, if the set of Grand Alliance $\{\cup_{i=1}^{k} B_i\}$ and Small Alliance $\{B_1, B_2, \ldots, B_k\}$ meets $\{\cup_{i=1}^{k} B_i\} \triangleright \{B_1, B_2, \ldots, B_k\}$, they can be merged. On the contrary, the Grand Alliance will split. During the above process, it will be continuously merged and split until all sub alliances reach a stable structure. Based on the above content, a schematic diagram of the CSS intelligent algorithm process integrating AG can be obtained, as shown in Figure 3.

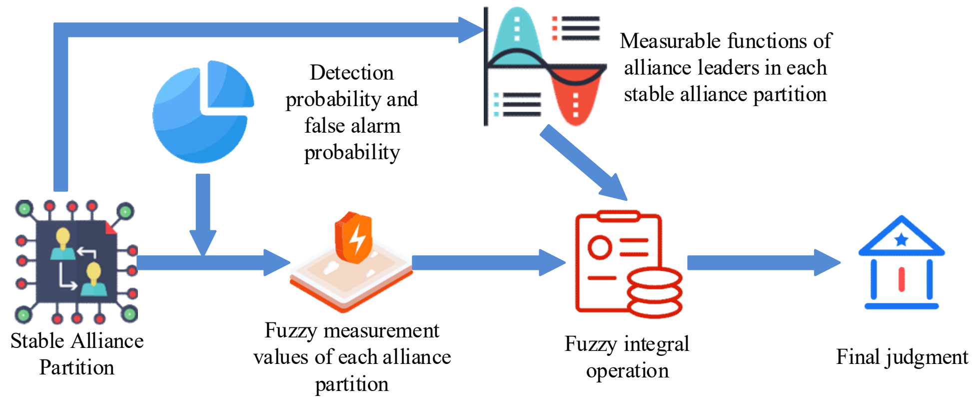


Fig. 3. Schematic diagram of CSS intelligent algorithm process integrating AG

In Figure 3, the $P_{n,b}$ and $P_{x,b}$ values of each satellite participating in the collaboration are first calculated. Then, the above satellites are regarded as independent sub alliances. Using the link negotiation and interaction information between satellites, the new alliance $VALUE(B)$ value is estimated. At the same time, changes are made according to comparison rules, merging rules, and splitting rules. After obtaining a stable structure, it can be stopped. Finally, fuzzy integration is used for fusion decision-making, that is, sub alliances with stable partitions will generate the alliance leader J values and corresponding historical detection values of all sub alliances and transmit them to the fusion center for decision-making, where the final decision result can be obtained.

2.3. CSS method for multi-satellite low orbit satellites based on MSCB and intelligent algorithms

With the increasing demand for communication in modern society and the development of satellite communication technology, satellite communication has gradually been widely applied in many traditional ground-based fields. Moreover, in recent years, the integrated information network of heaven and earth has become a new development direction for satellite communication, thus requiring more satellite access resources. However, at present, satellite spectrum resources are increasingly scarce, and the resource pseudo depletion is gradually emerging. At the same time, signal fading is a prominent problem in satellite communication, and spectrum resources are limited and non-renewable. In response to the above issues, the study first constructs a CSS system model for multi-satellite low orbit satellites, as shown in Figure 4.

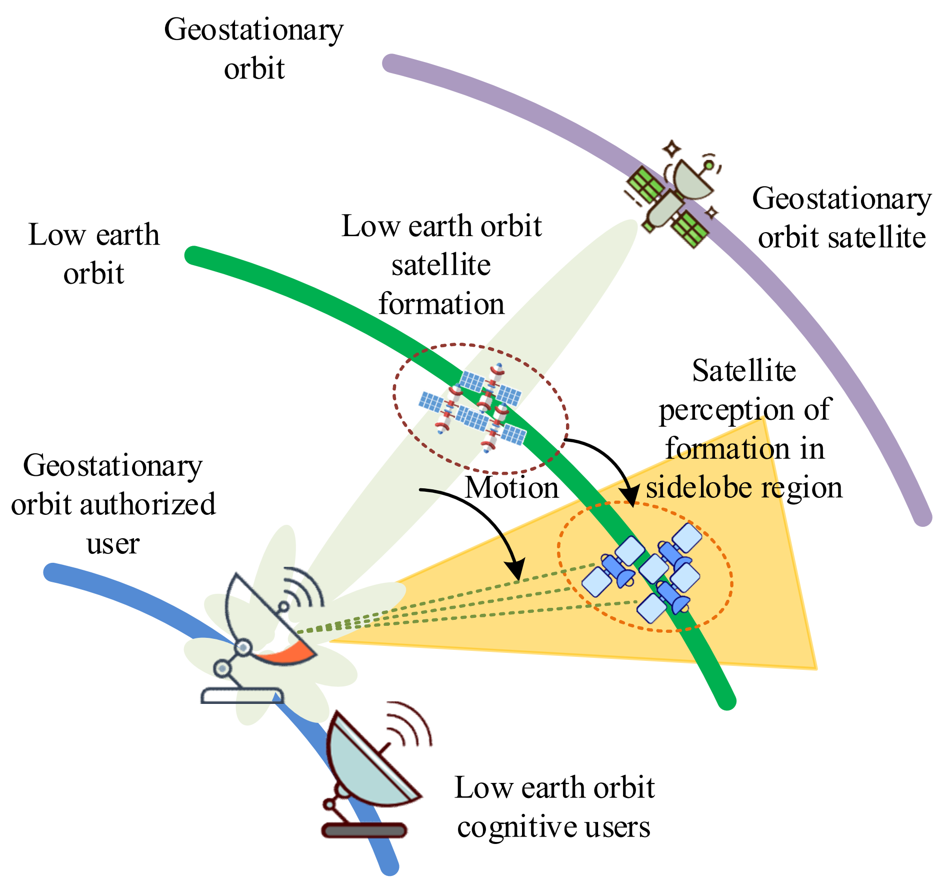


Fig. 4. CSS system model diagram of multi-satellite low orbit satellite

In Figure 4, the satellite network system and weak signal nodes on the ground are respectively regarded as cognitive networks and perceived target objects, while strong signal nodes are regarded as interference objects. Considering the presence of strong signal interference scenarios mentioned above, a CSS method for multi-satellite low orbit satellites based on MSCB and intelligent algorithms is designed to amplify the received power of weak signal nodes on the ground and suppress strong signal interference. Among them, MSCB technology improves the transmission quality and efficiency of signals through the collaborative work of multiple satellites. It is more suitable for low Earth orbit satellite networks because it can optimize signal coverage and transmission through beamforming, effectively managing inter satellite interference. And each cognitive satellite needs to adjust the direction and shape of the beam during the adjustment period to adapt to various communication needs. In this process, Genetic Algorithm (GA) is introduced to weight the cooperative sensing satellites of MSCB, and CCS intelligent algorithm is used to obtain the decision results, in order to improve the received signal-to-interference plus ratio in the multi-satellite cooperative sensing process. The MSCB technology is used to design a multi-satellite array. The distributed satellite cluster array model is shown in Figure 5.

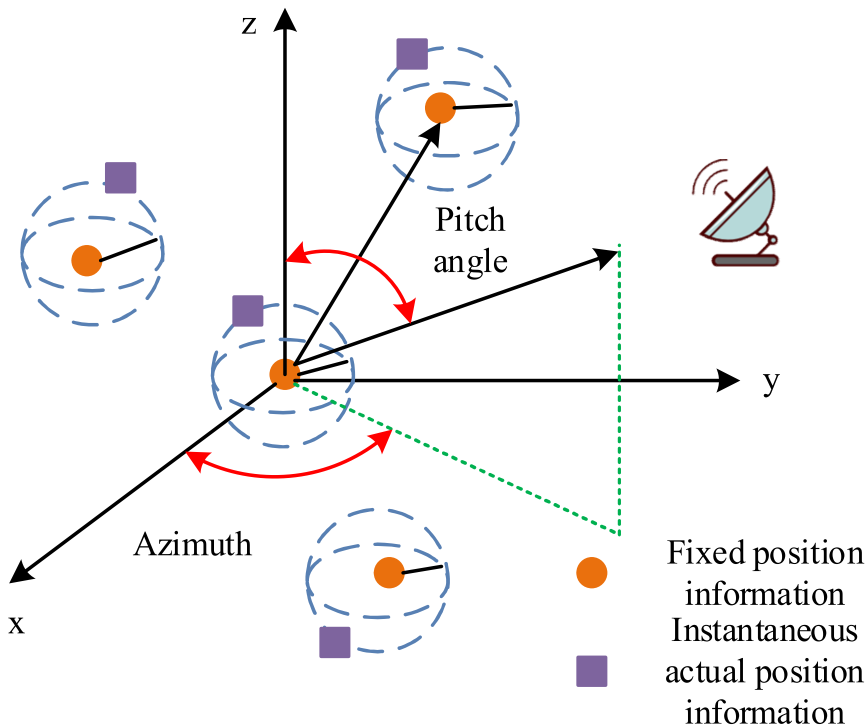


Fig. 5. Distributed satellite cluster array model

In Figure 5, there is a distributed formation satellite array model with D satellites, corresponding to pitch and azimuth angles, representing the initial set orbital position information of the satellites. However, in practical applications, satellites are subject to various factors that can cause corresponding instantaneous position offsets. The mathematical derivation process of MSCB technology applied to the CSS system model of multi satellite low orbit satellites is as follows. Assuming that the instantaneous position of the satellite is randomly distributed within a sphere with a radius of, centered on the determined position information. The instantaneous actual position is represented by the expected direction of the array directional graph function. From this, the following array conditions can be obtained. Firstly, each satellite array has the same antenna gain, and the corresponding expression is shown in equation (9).

$$R(\vartheta) = R_{\max}\left[\frac{O_1(\zeta)}{2\zeta} + 36\frac{O_3(\zeta)}{\zeta^2}\right]^2 \tag{9}$$

In equation (9), $O_1(\zeta)$ and $O_3(\zeta)$ correspond to the first and third order Bessel functions of the first type. ϑ represents the angle between the line connecting the satellite and ground nodes and the central axis of the beam. $R_{\max}$ is the maximum gain in the case of $\vartheta=0$. Secondly, when the distance between the satellite array and the ground node far exceeds the distance between the array satellites, the study approximates it as each satellite in a unified array experiencing the same link attenuation. Thirdly, the array satellites exhibit consistent synchronization in terms of time, phase, and frequency. In the weak signal direction, it is necessary to superimpose the guidance vectors of each cognitive satellite in the array in the same direction. Under the above conditions, the corresponding expression for the average power direction diagram P_A is shown in equation (10).

$$P_A = \left|F(\vartheta)\right|^2 \tag{10}$$

In equation (10), $F(\vartheta)$ represents the average directional pattern function of the satellite cluster array. The expression for $F(\vartheta)$ is shown in equation (11).

$$F(\vartheta)=\frac{1}{M}\sum_{n=1}^{M}W_n\bar{Q}_n(\vartheta) \tag{11}$$

In equation (11), W_n and $\bar{Q}_n(\vartheta)$ are the weighted values of cognitive satellites and the corresponding average guidance vectors of satellites, respectively. On the basis of the above methods, the G method is introduced to determine the satellite array with the best performance in multi-satellite cooperation scenarios. Finally, in the CSS section of MSCB, the specific content of the multi-node CSS method is shown in Figure 6.

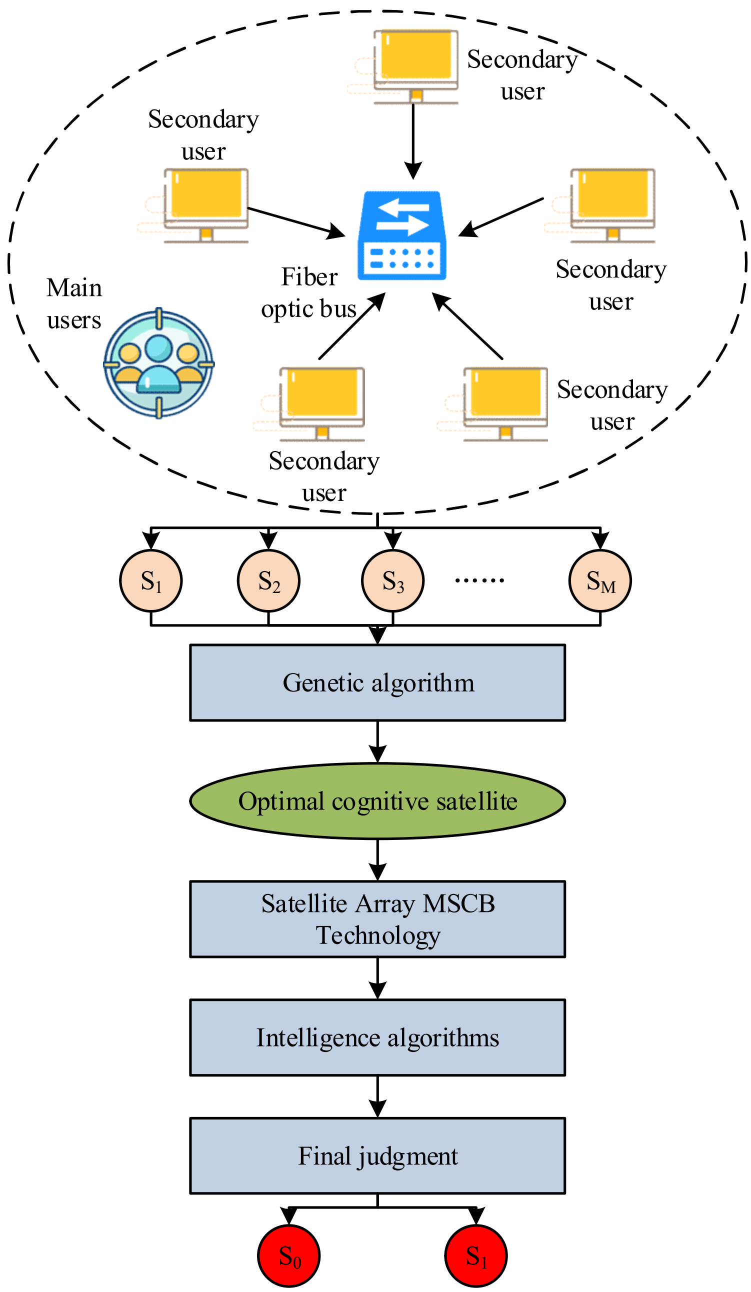


Fig. 6. Framework diagram of multi-node CSS method

In Figure 6, a central multi-node CSS model with a single authorized user and cognitive users is first studied. Then, the optimal cognitive satellite is determined through GA, processed using MSCB technology. Finally, the decision result is output through intelligent algorithm.

3. Result

3.1. Result analysis of CSS intelligent algorithm integrating alliance game

To verify the effectiveness and feasibility of the proposed intelligent algorithm, satellite simulation modeling and analysis software (Satelite Tool Kit, STK) are used for simulation. The false alarm rate generated during the detection process is ignored. At the same time, the Rice channel is used to improve the received signal to resist the adverse effects caused by fading, and the noise in the signal and transmission are Gaussian signal and Gaussian white noise, respectively. Finally, 2000 Monte Carlo experiments are conducted. The experimental parameters are set as follows: 500 sampling points, 5 participating cognitive satellite nodes, and random variables are used for the shadow Rice channel parameters. The simulation parameter settings for satellites and ground users are shown in Table 1.

Table 1. Simulation parameters of satellites and ground users

Parameter	Satellite system	
	Geostationary orbit	Low Earth orbit
Working frequency/GHz	12.5	
Satellite launch power/W	17	2.0
Satellite antenna gain/dBi	1.3	0.3
Satellite thermal noise temperature/K	300	
User antenna aperture/m	1.8	0.9
Antenna efficiency/%	60	
Track height/km	35786	1200
Satellite antenna aperture/m	1.8	0.9
Receiving signal drying ratio threshold/dB	0.1	
User antenna gain/dBi	42.8	36.8
Signal bandwidth/MHz	37	

To verify the performance of the research method more scientifically, comparative experiments are conducted using currently mainstream spectrum sensing methods, namely Dynamic Primary User Spectrum Sensing Based on Deep Learning (DPUSS-DL), Spectrum Sensing Based on Residual Neural Network (SS-RNN), and Collaborative Spectrum Sensing Based on Multi-Head Self-Attention Mechanism (CSS-MHSAM). In addition, commonly used parameters for evaluation include Detection Probability (DP), SNR, and Signal to Interference Plus Noise Ratio (SIPNR). Under the condition of P_x =0.1, the probability variation curves of correct detection for different algorithms and SNRs can be obtained, as shown in Figure 7.

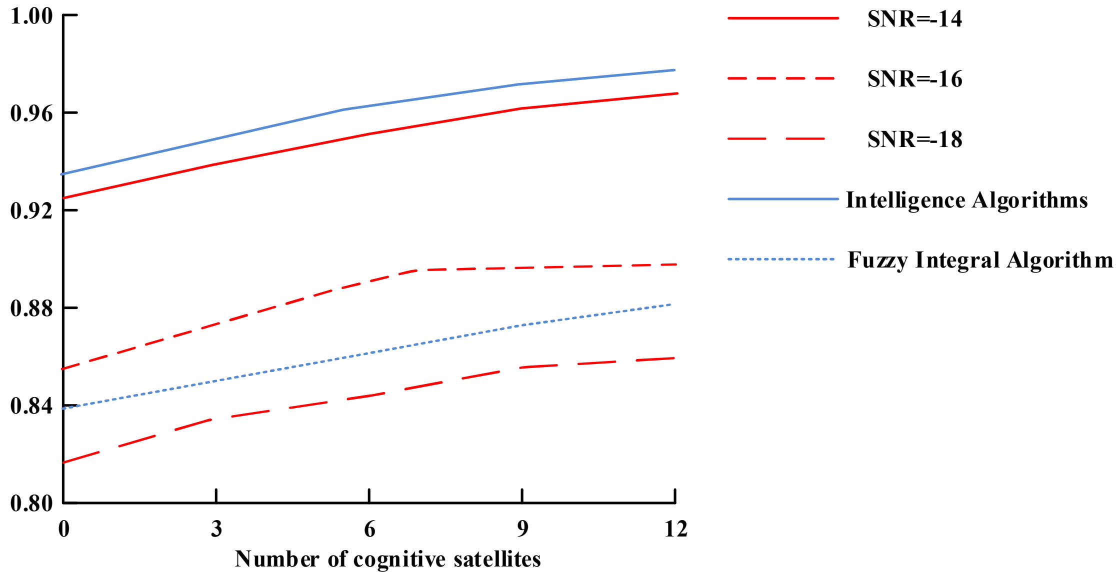


Fig. 7. Change curve of correct detection probability under different algorithms and signal-to-noise ratios

From Figure 7, it can be observed that all algorithms show a growing trend, indicating that the DP value increases with the increase of the number of collaborative satellites; And compared with the CCS algorithm based on fuzzy integration, the performance of intelligent algorithms has been significantly improved. In addition, the DP value of intelligent algorithms shows a more significant growth trend as the SNR value increases. The correct detection probability results of different methods in various SNRs are shown in Figure 8.

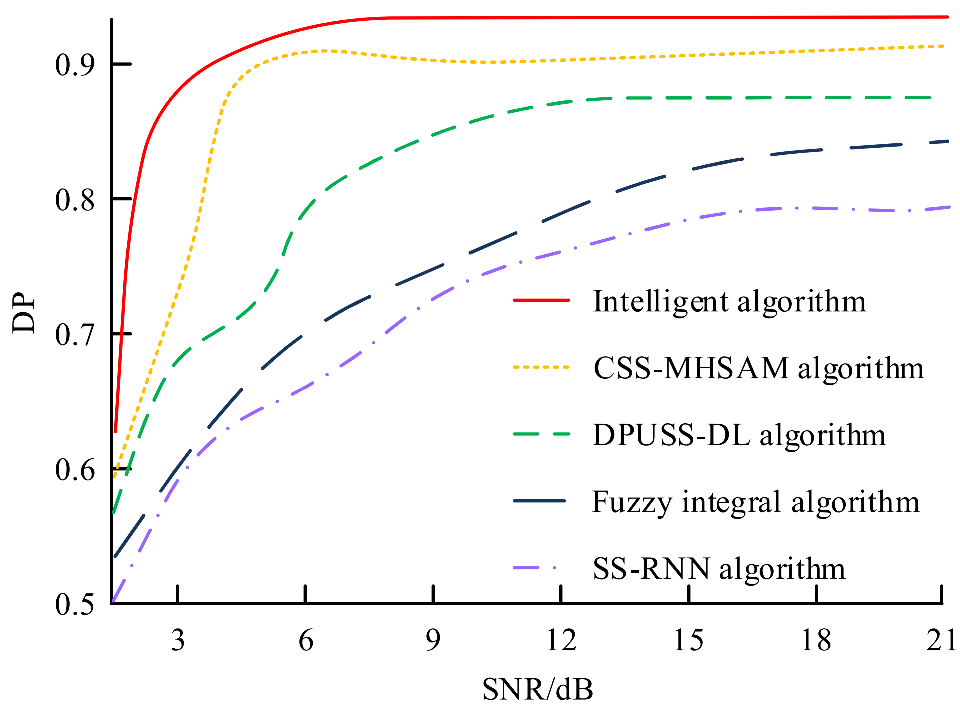


Fig. 8. The correct detection probability results of different methods in various signal-to-noise ratios

From Figure 8, the DP values and SNR results of each algorithm showed a positive correlation. The detection performance of the intelligent algorithm was the best, with significant advantages under low SNR conditions. When the SNR increased to -11dB, the DP value stabilized at 1. The performance of

SS-RNN algorithm and fuzzy integration algorithm was the worst, with corresponding DP values of 0.96 and 0.98 when the SNR reached 4dB. The above results may be due to the effective improvement of the v_i value in the fuzzy integral calculation process by the AG. To further analyze the comprehensive effectiveness and detection efficiency of different spectrum sensing methods, the Receiver Operating Characteristic (ROC) curve and detection time were used for evaluation. The results are shown in Figure 9.

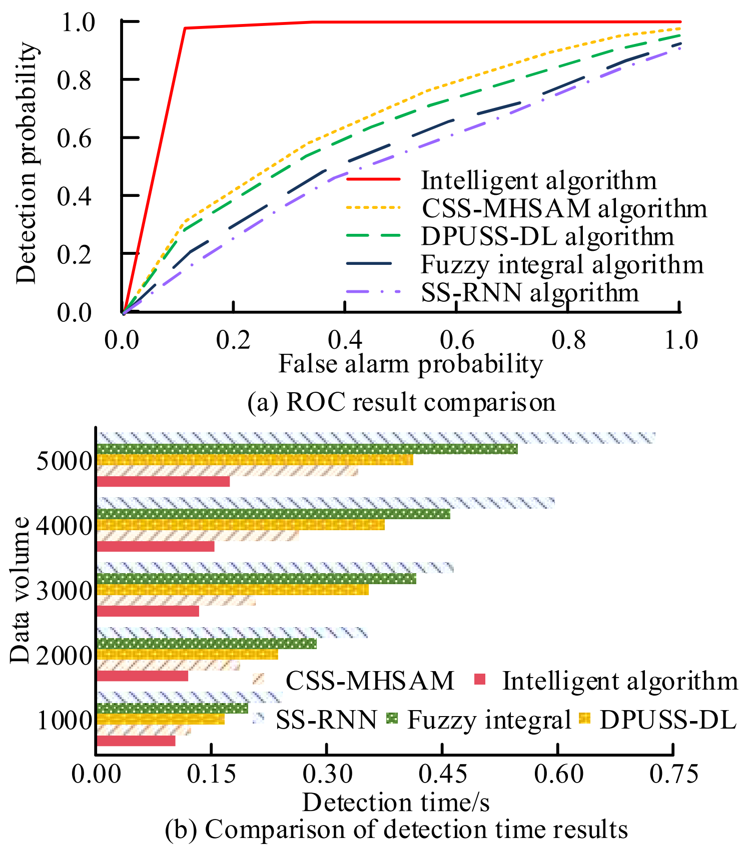
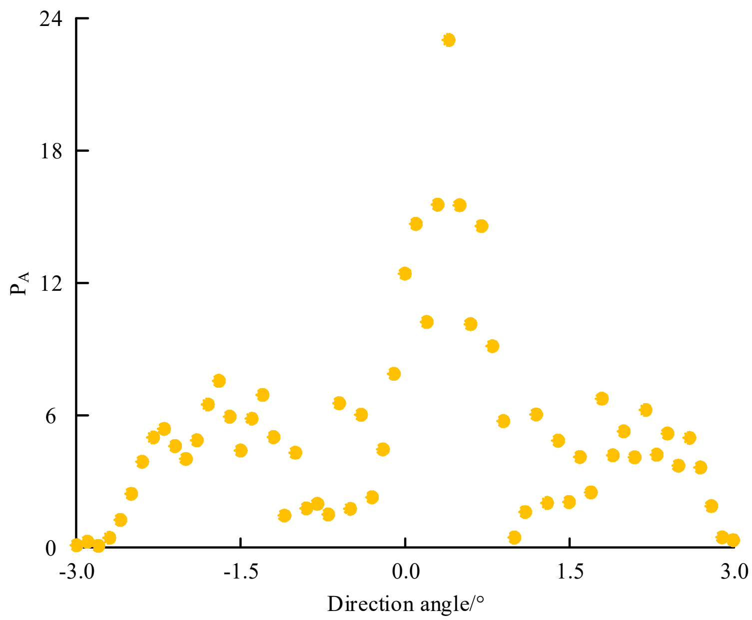


Fig. 9. ROC and detection time results of the same spectrum sensing method

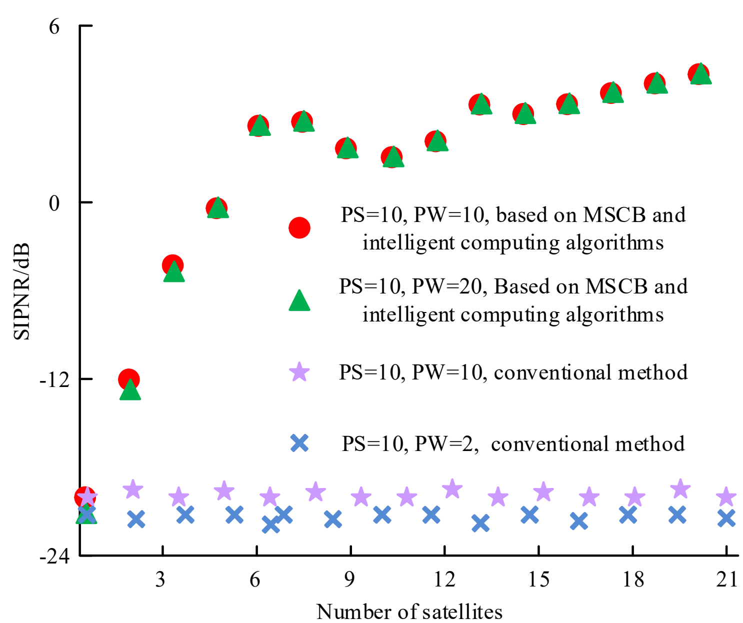
Figures 9 (a) and 9 (b) show the comparison of ROC and detection time results for different spectrum sensing methods, respectively. Figure 9 (a) shows a positive correlation between detection probability and false alarm probability, and the overall performance of the research method is significantly better than other mainstream spectrum sensing methods. When the false alarm probability is 0.1, the detection probabilities of intelligent algorithm, CSS-MHSAM algorithm, DPUSS-DL algorithm, fuzzy integral algorithm, and SS-RNN algorithm reach 0.98, 0.32, 0.29, 0.22, and 0.17, respectively. When the detection probability is 0.9, compared with other mainstream algorithms, the false alarm probability of intelligent algorithms is reduced by more than 70%. The above results are generated because intelligent algorithms can effectively improve the reception power of several cooperative satellites for weak signals while ensuring the suppression of strong interference, thereby achieving the effect of multi satellite low orbit satellite cooperative perception of weak signals. As shown in Figure 9 (b), with the continuous growth of training data, the time consumed by intelligent algorithms is relatively shorter, and in the case of larger data, the convergence time required by the algorithm will be relatively less. Therefore, it is very suitable for fast operations on large-scale data.

3.2. Analysis of CSS method for multi-satellite low orbit satellites

To analyze the superiority of the multi-satellite low orbit satellite CSS method based on MSCB and intelligent algorithms in scenarios with strong interference signals and weak signal nodes, this study compares it with conventional CSS fusion criteria method. In the above scenario, the simulation parameters are set as follows. The number of satellites is set to 125, the strong signal interference direction conforms to (90°, 0.5°), the maximum iteration number of the GA is set to 500, and the strong and weak signal nodes have the same transmission gain, both of which are 1. The transmission power of the strong interference signal node P_s and the weak signal node P_w are 10dBm and 30dBm, respectively. P_x is set to 0.1. The performance change curve of the satellite array is shown in Figure 10.



(a) P_A variation curve of satellite array



(b) SIPNR variation curves of satellite arrays under different methods

Fig. 10. The capacitance and voltage fluctuation curves at various temperatures

Figure 10 (a) shows the P_A variation curve of the satellite array. When the satellite perturbation radius was 15m, the sub generated by P_A in the direction of strong interference signals was consistently 1.7e-3, indicating that the research method can effectively suppress strong interference signals in the perception process. Figure 10 (b) represents the SIPNR variation curves of satellite arrays under different methods. As the number of participating satellites increased, the SIPNR value of the research method in perceiving weak ground signal nodes with strong signal interference also constantly increased. Compared with conventional methods, the research method has higher SIPNR values throughout the entire process. This indicates that the research method is more effective when there is a small difference in transmission power between the transmitted signal and the interference signal. The probability variation curve of satellite array detection is shown in Figure 11.

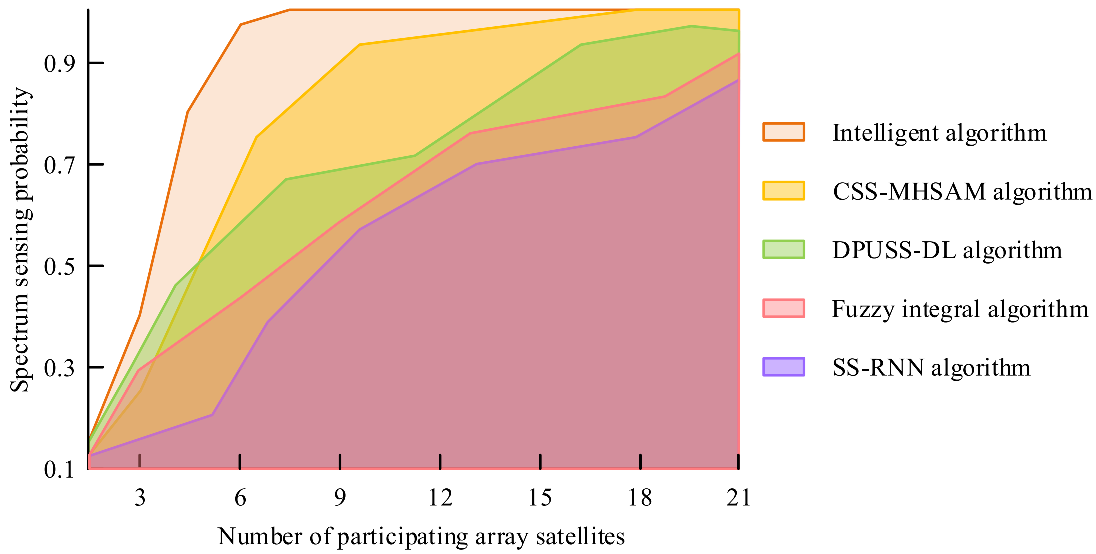


Fig.11. Probability variation curve of satellite array detection

As shown in Figure 11, in the scenario of weak ground signal nodes with strong interference, different methods showed a continuous upward trend in DP values as the number of satellites participating in the array increased. When the number of participating satellites in the array was 10, the DP value of the research method tended to be close to 1, while the DP value of the conventional method did not exceed 0.9 at the highest. This indicates that the research method can effectively deal with strong interference signals and improve the receiving power of cooperative satellites for weak signal nodes, thus exhibiting excellent perceptual performance in applications. In addition, the detection performance of the research method is better when the transmission power of the strong interference signal node is similar to that of the target node perceived on the ground. Based on the above analysis and GA optimization, the optimal satellite array diagram can be obtained, as shown in Figure 12.

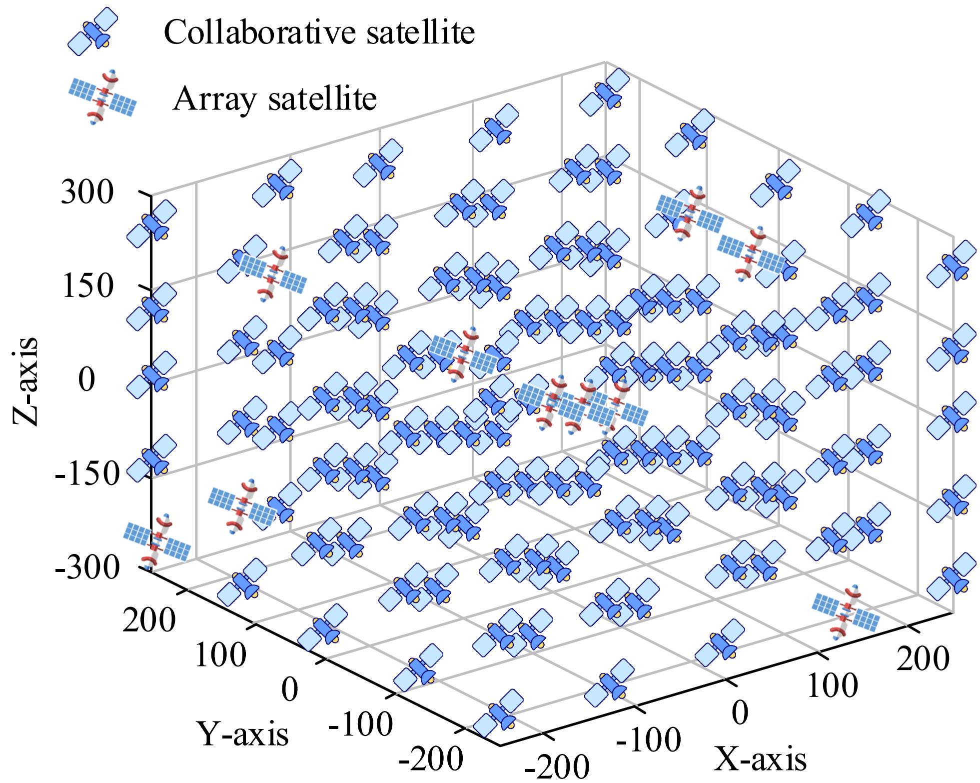


Fig. 12. Schematic diagram of optimal satellite array

From Figure 12, the satellite array included 10 array satellites and several cooperative satellites. Through calculation, the power utilization rate of the satellite array reached 93.4%, indicating that the research method can reduce the interference of ground users and alleviate frequency shortage in space network systems.

4. Conclusions

Cognitive radio technology determines the priority direction of future frequency resource development and utilization. It is crucial for fair access to spectrum resources, global wireless communication industry development, and coordinated development of different wireless services. Due to the current shortage of satellite spectrum resources, a CCS algorithm based on fuzzy integration was proposed. It was combined with AG to obtain an intelligent algorithm. Finally, a multi-satellite low orbit satellite CSS method based on MSCB and intelligent algorithm was designed. The experimental results showed that the intelligent algorithm maintained a stable DP value of 1 when the SNR increased to -11dB. The performance of SS-RNN algorithm and fuzzy integration algorithm was the worst, with corresponding DP values of 0.96 and 0.98 when the SNR reached 4dB. In the scenario of weak ground signal nodes with strong interference, when the number of participating satellites in the array was 10, the DP value of the research method tended to be close to 1, while the DP value of the conventional method did not exceed 0.9 at most. The optimal satellite array power utilization rate obtained from the final solution reached 93.4%. In summary, the research method can effectively enhance the spectrum sensing capability of low orbit satellite systems and provide technical support for frequency utilization strategies of other satellite communication networks. However, there are still shortcomings in the research. The research method has not taken into account the effects of multi-satellite synchronization errors and blind node perception. Therefore, in future research, the impact of these factors can be comprehensively considered to improve the actual deployment of satellites.

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