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RESEARCH ARTICLE

Spectrum Sensing Algorithm by Multi-Objective Optimization Theory and Fuzzy Integral Method

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ABSTRACT As spectrum resources become increasingly scarce, efficient spectrum management is crucial in wireless communication. To address this challenge, a new spectrum sensing algorithm based on multi-objective optimization theory and fuzzy integral method has been developed. This innovative algorithm combines the whale algorithm and fuzzy integral algorithm, allowing for multi-objective optimization and interference decision-making. It overcomes limitations in existing multi-user spectrum sensing methods, such as low perception probability, poor detection accuracy, high false alarm probability, and computational complexity. Comparative studies show that the multi-objective whale algorithm achieves excellent optimization performance and fast convergence, reaching a throughput of 16.8 after 600 cycles. The collaborative spectrum sensing method, especially the one based on fuzzy integration, performs exceptionally well, particularly in high signal-to-noise ratio environments. This algorithm has significant application potential and effectively addresses spectrum resource management in wireless communication. It offers benefits such as improved spectrum utilization efficiency, scalability, and practicality, making valuable contributions to technological progress and efficiency enhancement in the field.

INDEX TERMS Whale algorithm, fuzzy integral method, spectrum sensing, multi objective optimization theory, interference decision.

I. INTRODUCTION

As communication technology develops, higher requirements for wireless communication rises, and the demand for wireless communication bandwidth is also increasing. At present, radio spectrum resources are increasingly scarce. How to effectively use the limited spectrum resources and improve the spectrum utilization has become an urgent problem. Cognitive radio technology can use the spectrum resources occupied by unauthorized users for communication services to solve spectrum resource shortages [1], [2]. Cognitive radio system wakes up the primary user by transmitting wireless signals in the idle frequency band, so that the primary user can use these idle frequency bands. In cognitive radio system, spectrum sensing technology is a very important link, it is the key to cognitive radio technology. As cognitive radio technology develops, some new spectrum sensing algorithms have been proposed, but these algorithms have the problems of low sensing probability, poor detection accuracy, high false alarm probability, and high computational complexity [3], [4]. Using multi-objective optimization theory and fuzzy integral method, a spectrum sensing algorithm is proposed [5], [6]. By utilizing fuzzy integration methods, issues such as signal uncertainty and noise interference can be better managed, thereby enhancing detection performance and accuracy. Through the application of multi-objective optimization techniques, an optimal trade-off can be achieved among multiple objectives. This can potentially contribute to optimizing spectrum utilization and consequently improving spectrum efficiency. By employing efficient algorithms, the computational complexity of the problem can be reduced, thus enhancing the real-time capability of the spectrum sensing algorithm. The research includes four parts. The first part is the overview of the spectrum sensing algorithm using multi-objective optimization theory and fuzzy integral method. The second part is the research of the spectrum

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sensing algorithm model. The third part is the experimental verification of the second part. The fourth part is the summary of the research content and points out the shortcomings.

II. RELATED WORKS

As an emerging technology, spectrum sensing technology has always been a research hotspot in cognitive radio. Different from traditional static spectrum sensing algorithms, the spectrum sensing algorithm using cognitive radio needs to detect the signal of the primary user to obtain current channel spectrum resources when the primary user has not used the authorized frequency band. Therefore, using intelligent, efficient, accurate, and robust sensing algorithms to improve the utilization of spectrum resources and system reliability should be solved in cognitive radio. The multi-objective optimization method adopted by B Lin et al. Can effectively improve the overall performance of the structure. The multi-objective optimal design method for structural performance has been developed rapidly. But the methodology of BPO still needs to be improved. Among them, the interaction between optimization and decision-making is weak, which makes the optimization efficiency low and restricts its promotion in product development. To solve this problem, this project will study a preference-based multi-objective BPO method, which can achieve 100% of the "preference" in 2600 simulations, while the non-preference method can achieve only 24% of the "preference" in 60000 simulations. On this basis, two evaluation methods of "preference satisfaction" and "difference measure" are introduced for the first time to evaluate the quality of the optimal solution. It will provide a theoretical basis for the development of BPO methods and provide better services for customers [7]. Hernandes A G's research team planned to use the convolutional neural network (CNN) method to train a large number of uncalibrated antennas of the system user (SU) sharing the same frequency, and test their performance. The CNN framework was proposed to make it robust by extracting features from the sample covariance matrix. On this basis, the CNN-SS algorithm was compared with the current eight major multi-antenna signal strength detection algorithms, including the John detector, sphericity detector, generalized likelihood detection algorithm, local strongest invariance detection algorithm, etc. It was compared with the five extended algorithms based on a convolutional neural network. The Monte Carlo calculator (MCS) was used to verify its performance [8]. M Karimi and others intend to study spectrum sensing and resource optimization in multiband cognitive radio (CR) systems. On this basis, an optimal solution was proposed to maximize the CR transmission rate under the conditions of interference, and a non-convex optimal solution was obtained. Because the original formal optimization problem was nonconvex, it was transformed into a convex problem to obtain the best result using the Lagrange multiplier method and linear programming method [9]. C Li et al. proposed a better solution by effectively solving the multi-objective optimization. Grey correlation degree is an effective method, which can effectively evaluate it. In the multi-objective optimization problem, the weighted distribution was an important part of decision-making. In addition, because the calculation of the grey correlation degree was limited to the training sample size, the accuracy of the optimization results was low. In view of the above problems, this project planned to use the method of combining entropy weight theory, etc. to carry out multi-objective optimization on the original defects, and determine the optimal processing scheme in order. Firstly, Three optimal indexes of specific energy, surface finish, and machining efficiency of the machine tool were determined. On this basis, the weight of each optimization objective was allocated by using the principle of information entropy [10]. D Han's research team, in the case of large infeasible area, gave consideration to the relationship between optimal objectives and satisfying constraints. To solve this problem, the fuzzy set theory method was proposed to accurately describe the difference between the objective function and the degree of constraint violation. Then, a new concept of "fuzzy advantage" was proposed to comprehensively measure the advantages and disadvantages of an optimal solution, so that the optimal solution cannot exist. Finally, the effectiveness of the proposed method was demonstrated through an example. Compared with 9 kinds of MOEA in the world, the proposed multi-objective complementary optimization method had good performance in solving multi-objective complementary problems [11].

Thareja Y and other scholars planned to adopt a new spectrum sensing technology to comprehensively optimize the network lifetime, energy consumption, and message transmission. On this basis, a communication mode based on inter-group and intra-group was proposed, and on this basis, a new spectrum sensing method was studied. In this experiment, active nodes, dead nodes, persistent energy, and data packets sent to the base station were tested. The experimental results showed that under different algorithms, the average spectrum sensing effect was 0.9060, the FMODE algorithm was 0.9197, NSGA was 0.9343, the least square method was 0.9915, and the proposed algorithm was 0.9738. The experimental results showed that this algorithm was much better than the existing algorithms [12]. T Shiba et al. used a new method to realize the spectrum reconstruction and demodulation of multiple actual RF down-sampled signals. Because its circuit structure was relatively simple, many RF spectrum reconstruction algorithms based on it were proposed. A new method using multiple clocks and a continuation algorithm to realize direct sampling of real signals was proposed. Computer simulation showed that the proposed algorithm was feasible. Through simulation and actual measurement, it was proved that the method was effective and also used in demodulation systems [13].

To sum up, Indeed, fuzzy integral methods and multi-objective optimization theories have been applied in many fields, yet substantial challenges remain in the spectrum sensing algorithm where traditional applications are scarce. Early research on spectrum sensing algorithms primarily focused on energy detection, matched filter detection, and cyclostationary feature detection techniques. These methods, although essential, had limitations in their sensitivity and adaptability to dynamic spectra environments. Lately, contemporary research has aimed at incorporating fuzzy integral methods and multi-objective optimization theories into the spectrum sensing algorithm. This integration has provided a refined approach to handling spectrum sensing anomalies, avoiding inaccuracies prevalent in traditional methods and ensuring efficient, optimal utilization of the spectrum. Consequently, in this study, traditional fuzzy integral algorithms and multi-objective optimization theories were used as a foundation for infusion into the spectrum sensing algorithm. This amalgamation led to optimization and consequently an enhancement in the precision of the spectrum sensing algorithm. Therefore, this integration marks a significant milestone in spectrum sensing algorithm development, essentially bridging the gap between early and contemporary research approaches. The fusion strategy provides a promising pathway for future studies to address the complexity and necessity of guaranteeing optimal and efficient spectrum utilization. The fuzzy integral method and multi-objective optimization theory have been applied to many fields, but in the research process, there are still many problems, and the traditional fuzzy integral algorithm and virtual multi-objective optimization theory are rarely applied to spectrum sensing algorithms. Therefore, this research is based on the traditional fuzzy integral algorithm and multi-objective optimization theory, and the realization is integrated into the spectrum sensing algorithm and optimized, so as to improve the algorithm's accuracy.

III. SPECTRUM SENSING ALGORITHM MODEL CONSTRUCTION BASED ON MULTI-OBJECTIVE OPTIMIZATION THEORY AND FUZZY INTEGRAL METHOD

With the increase of the limitation and competitiveness of radio spectrum, effective sensing and optimization of spectrum utilization is very important to ensure the performance of communication systems. In this context, the combination of multi-objective optimization and fuzzy integral to establish the mathematical model of spectrum sensing has become the current research focus. In this chapter, its architecture and theory are the core, and its challenges and future are discussed in the current spectrum management system.

A. SPECTRUM SENSING ALGORITHM CONSTRUCTION INCORPORATING MULTI-OBJECTIVE OPTIMIZATION PRINCIPLE

With the increasing compression and competition of radio spectrum, real-time sensing and optimization of spectrum utilization become more and more important. In this field, the construction of the spectrum sensing algorithm based on pyramid multi-objective optimization is a very promising method. Considering the distribution of solutions in the target space and the selection of fitness function, the whale algorithm is proposed by integrating the multi-objective optimization algorithm. In a particular case, the relative ability of individuals to pass on their genes to their offspring is called fitness [14], [15]. The management of spectrum resources typically involves multiple objectives, such as enhancing system throughput and reducing interference effects. These objectives may conflict with each other, necessitating the identification of a set of balanced solutions. Multi-objective optimization problems are often intricate, requiring the development of optimization algorithms capable of considering multiple objectives simultaneously. According to the characteristics of the difficulty of sub-target weighting and the hierarchical division of labor in a pyramid structure, the fitness function is first initialized and its fitness value is calculated, then it is sorted and layered by fitness value size. And finally, the fitness function is updated according to the selected optimal and suboptimal individuals, so as to generate a secondary fitness function more suitable for the promotion of individuals at each level, the initial fitness function, As shown in formula (1).

$$F\left(X\right) = \lambda_1 F_1\left(X\right) + \lambda_2 F_2\left(X\right) \tag{1}$$

In formula (1), $F_1\left(X_1\right)$ and $F_2\left(X_2\right)$ respectively represent the optimal fitness values of the first sub-target and the second sub-target, and the calculation of traction gradient is shown in formula (2).

$$\begin{cases} \lambda_1 = \dfrac{\beta_1}{\beta_1 + \beta_2} \\ \lambda_2 = \dfrac{\beta_2}{\beta_1 + \beta_2} \end{cases} \tag{2}$$

In formula (2), λ_1 and λ_2 represents the sum of traction gradients in two directions, β_1 and β_2 represents the traction amount of the two sub-targets to the individual X respectively. However, in practical application, due to certain constraint relationships between groups, the target value cannot always be constant, which makes the calculation result deviate greatly from the actual situation [14]. The evolutionary gradient under each target is shown in formula (3).

$$\begin{cases} \alpha_1 = \dfrac{\left|F_1\left(X_1\right) - F_2\left(X_2\right)\right|}{\left\|X_1 - X_2\right\|_2} \\ \alpha_2 = \dfrac{\left|F_1\left(X_1'\right) - F_2\left(X_2'\right)\right|}{\left\|X_1' - X_2'\right\|_2} \end{cases} \tag{3}$$

In formula (3), α_1 and α_2 represent the gradient size, and then are normalized to obtain the adaptive evaluation criteria, as shown in formula (4).

$$F_{n+1}\left(X\right) = \delta_1 F_1\left(X\right) + \delta_2 F_2\left(X\right) \tag{4}$$

In formula (4), $F_{n+1}\left(X\right)$ is the fitness function at $n+1$ iteration of the current target layer. The combination of traction gradients in both directions is shown in formula (5).

$$\begin{cases} \delta_1 = \dfrac{\alpha_1}{\alpha_1 + \alpha_2} \\ \delta_2 = \dfrac{\alpha_2}{\alpha_1 + \alpha_2} \end{cases} \tag{5}$$

In formula (5), δ_1 and δ_2 represent the combination of traction gradients in two directions. By analogy with the initial function of the above objective, when there is x objective function, it is shown in formula (6).

$$F(X) = \sum_{j=1}^{x} \lambda_j F_j(X) \tag{6}$$

Levy Flight is a method that has been widely verified in nature. The flight paths of many animals conform to the *Levy* distribution, and *Levy* flight is the optimal search method when there is "no preferred direction" and the location is unknown and cannot be completed. This method not only increases the search radius of the individual, but also increases the search area of the individual, so that it will not fall into local extremum, so as to improve the probability of obtaining the optimal solution. Position information of levy mutation is updated, as shown in formula (7).

$$k_i^{t+1} = k_i^t + \delta \oplus Levy(\varepsilon) \tag{7}$$

In formula (7), k_i^t is the solution of i position of t population generation, δ controls the search step size and is greater than 0. $\oplus$ is point-to-point multiplication and $Levy(\varepsilon)$ is the *Levy* search path of the parameter ε. *Levy* is subject to Levy distribution in formula (8).

$$Levy(\varepsilon) \sim \frac{u}{|v|^{1/\varepsilon}} \tag{8}$$

In formula (8), u and v obey normal distribution. First, the reverse learning method is introduced into the initialization process of the population to improve population diversity and prevent the algorithm from falling into local extremum; Secondly, through the calculation of the Pareto ranking and crowding distance of the population, 10% of the individuals are selected from the first-order Pareto frontier solution as the global leader, and the diversity of the population is obtained through reverse learning method, and *Levy* mutation is introduced between the candidate population and the reverse candidate population to produce offspring. After this process, the Pareto optimal solution is finally obtained [16], [17]. The evolution process of the population hierarchy is shown in Figure 1.

In Figure 1, the purple dotted line is the Pareto optimal frontier, U is the basic individual. Through the guidance of ε_1, it is promoted to the organizational level to generate individuals U_1 with better fitness. Similarly, as iterations increase, individuals at the bottom will continue to rise to the top, while the populations at other levels will also evolve according to this method. Finally, the population will gradually approach the Pareto optimal frontier. It is easy to fall into local optimization in the late stage of multi-objective optimization. Therefore, expand the individual search radius of the basic layer, and adopt the competition mode that new individuals directly replace the old ones to ensure the randomness of the population, and continuously promote to avoid the local optimal situation. The whale algorithm iteratively explores the search space to progressively optimize solutions. In each iteration, new solutions are selected by incorporating comprehensive evaluations using fuzzy integration. The whale algorithm is a heuristic optimization technique inspired by the behavior of whale populations. It is capable of seeking optimal solutions within the search space, though adjustments to algorithm parameters and convergence need to be considered in practical applications. Figure 2 shows the flow chart of the improved whale algorithm.

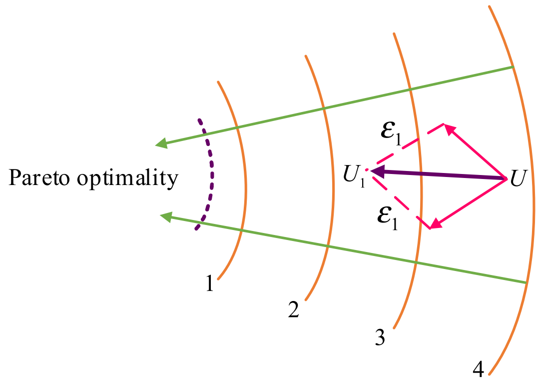

FIGURE 1. Evolution process of population hierarchy.

In Figure 2, to ensure the convergence of the whale algorithm towards stable solutions during the iteration process, adjustments to algorithm parameters might be necessary. This balancing of global exploration and local exploitation aims to fine-tune the algorithm's performance. the improved whale algorithm has high search accuracy, fast convergence speed, and strong stability. The improved whale optimization algorithm solves the optimal value function and actual function problems, and good results are obtained by a large number of experiments, which provides certain theoretical support for the application of the algorithm [18], [19].

B. SPECTRUM SENSING ALGORITHM MODEL INTEGRATED WITH FUZZY INTEGRAL METHOD

The research of cooperative spectrum sensing algorithms using fuzzy integral is a field worthy of further exploration. In cooperative spectrum sensing, cognitive users' perception information will be affected by a variety of interference factors, resulting in some uncertainty in the perception information, that is, fuzziness. The cooperative spectrum sensing algorithm based on fuzzy integral can effectively deal with uncertain sensing information. Through fuzzy reasoning and fuzzy clustering, the fuzzy information is transformed into reliable spectrum usage information, so as to improve the accuracy and efficiency of spectrum sensing. In addition, the algorithm also uses cooperative sensing, that is, through information sharing and cooperation among multiple cognitive users, it improves the coverage and data stability of spectrum sensing, and ensures the efficient utilization of network resources. In short, this algorithm is an effective spectrum sensing technology, which can be applied to mobile

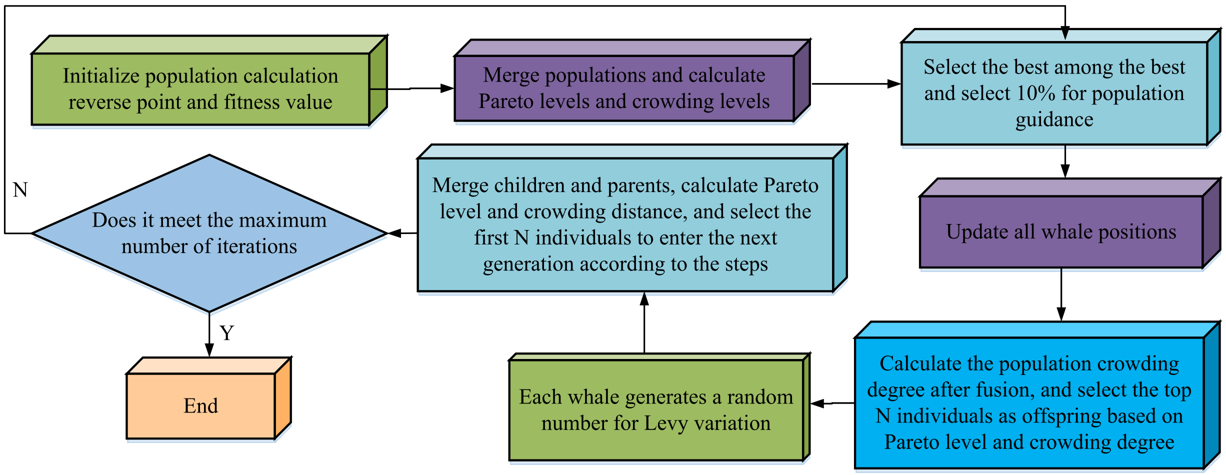

FIGURE 2. Improved wheel algorithm flowchart.

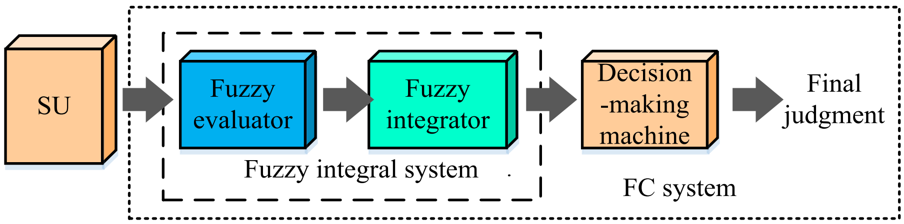

FIGURE 3. The processing process of fuzzy integral system.

communication, wireless network, the Internet of Things, and other fields, and has a wide application prospect [20], [21].

At present, the spectrum sensing algorithm model based on the fuzzy integral method has become a new solution in the field of radio communication. This is because the algorithm model can detect and predict the spectrum usage and change process more accurately. In contrast, although the traditional spectrum sensing algorithm model can make certain identification and prediction of the spectrum, it is often difficult to obtain more accurate spectrum information because of its simple calculation method. Therefore, from the effect point of view, the spectrum sensing algorithm model based on the fuzzy integral method has more advantages than the traditional algorithm model in the field of radio communication and is expected to be widely used in the future. A cooperative spectrum sensing method is provided, as shown in Figure 3.

In Figure 3, after completing the local spectrum sensing and making corresponding assumptions by the presence or absence of the primary user signal, the fusion center performs fuzzy integral processing on the detected calculation data for each sensing user. For two types of assumptions, i.e. with or without primary user signal, two types of fuzzy integrals are set respectively, i.e. Fuzzy Integrals with primary user signal and fuzzy integrals without primary user signal, and two fuzzy measures are set in each type of fuzzy integrals; Then, a different fuzzy evaluation method is set for each fuzzy measure; On this basis, by comparing two kinds of training sequences with or without primary user signal, the optimal value of four kinds of fuzzy measures is obtained by using the optimal algorithm; Finally, using the best fuzzy measure value, the fuzzy integral value of the statistics detected by each user under two different fuzzy integrators is obtained [22]. In the CR system, the received signal detected by the cognitive user (CU) is shown in formula (9).

$$\begin{cases} H_0 : y_i\left(t\right) = n_i\left(t\right) & i = 1, 2, \ldots, N \\ H_1 : y_i\left(t\right) = h_i \times x\left(t\right) + n_i\left(t\right) & i = 1, 2, \ldots, N \end{cases} \tag{9}$$

In formula (9), $x\left(t\right)$ is the transmitted signal, h_i is the channel gain, $n_i\left(t\right)$ is the Gaussian white noise, and $y_i\left(t\right)$ is the signal received by Cu. According to the central limit theorem, it follows the Gaussian distribution, as shown in formula (10).

$$\begin{cases} \mu_0 = N, \sigma_0^2 = 2N \\ \mu_1 = N\left(1+\gamma\right), \sigma_1^2 = 2N\left(1+2\gamma\right) \\ \gamma = {}^{P_x}/{}_{P_n} \end{cases} \tag{10}$$

In formula (10), μ_0 and μ_1, σ_0^2 and σ_1^2 are the mean and variance respectively, σ_1^2 is the average power of noise, P_x is the average power of signal, and γ is the signal-to-noise ratio (SNR) of CU output. Among them, the node responsible for collecting data plays the role of data fusion and converts it into the final decision. On this basis, a fuzzy metric algorithm

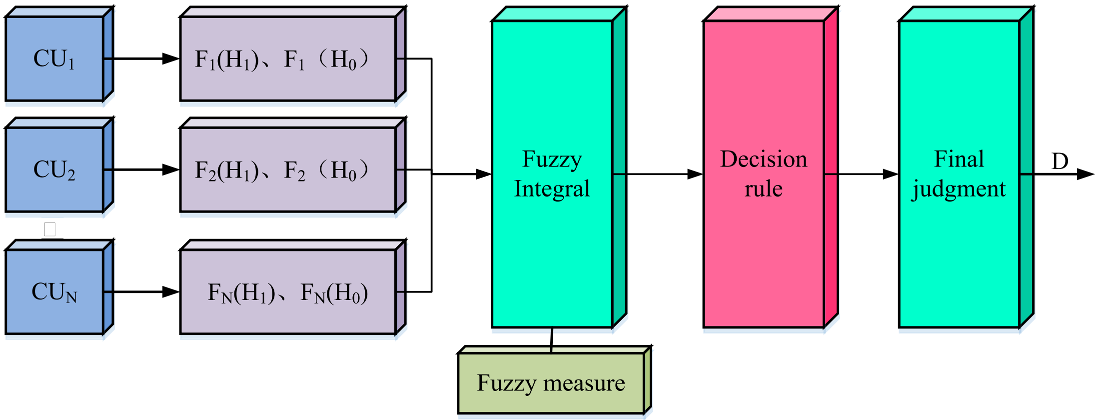

FIGURE 4. A spectrum perception framework based on fuzzy integral.

solves multi-classifier data fusion. According to the known information of SNR, the confusion matrix is shown in formula (11).

$$CM_i = \begin{bmatrix} 1 - P_f^i & P_f^i \\ P_m^i & P_d^i \end{bmatrix} \tag{11}$$

In formula (11), the confidence degree can be calculated according to the confusion matrix CM_i, and its fuzzy measure e_i can be measured. According to the membership matrix, the spectrum sensing framework can be measured, as shown in Figure 4.

In Figure 4, after each CU has sent the local decision data, that is, the membership of the primary user signal is detected this time, the fusion center will fuzzily integrate it with the obtained fuzzy measure to obtain the final membership value, and then determine the mechanism according to the maximum membership principle to make the final decision. Uncertainty factors are common in communication systems, and fuzzy integral algorithms can comprehensively evaluate these uncertainty factors. However, how to combine fuzzy integral with the whale algorithm to make the evaluation more accurate is a challenge.

C. SPECTRUM SENSING MODELING USING FUZZY INTEGRAL AND MULTI-OBJECTIVE OPTIMIZATION THEORY

In the field of spectrum sensing, spectrum sensing modeling using fuzzy integral and multi-objective optimization theory is an important research topic. This modeling method combines fuzzy integral and multi-objective optimization ideas, aiming to achieve accurate spectrum use information extraction and optimization decision. At the same time, the fuzzy integral theory can effectively process and transform the fuzzy sensing information, so as to improve the accuracy and reliability of spectrum sensing. Theory's main idea is to transform the fuzzy sensing information into reliable spectrum usage information through fuzzy reasoning and fuzzy clustering and provide accurate data support for subsequent optimization decisions. The proposed algorithm needs to undergo performance analysis through experimentation to validate its effectiveness. It is essential to establish an appropriate experimental environment and evaluation metrics, conducting comprehensive experiments to validate the superiority of the algorithm. Evidence theory can be applied to spectrum sensing. The spectrum sensing model of the CR system is shown in Figure 5.

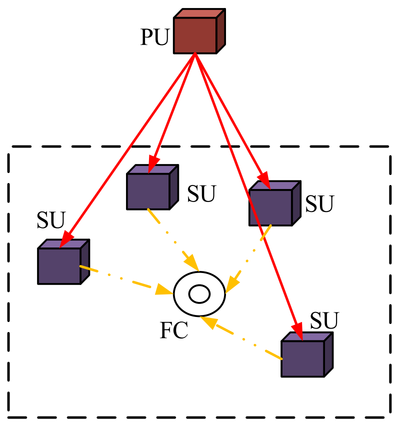

FIGURE 5. CR system spectrum perception model.

In Figure 5, each SU applies energy detection to conduct local spectrum sensing respectively and makes two kinds of assumptions by PU signal, namely, PU signal exists and PU signal does not exist. At the same time, in the CR system of cognitive radio, the detection target signal of any sensing user is shown in formula (12).

$$Y_j = \sum_{i=1}^{m} \left| X_{ij} \right|^2 \tag{12}$$

In formula (12), X_{ij} is the i sampling value in the received signal of the j sensing user, and i is the serial number of the sampling point, m is the total number of sampling points of the received signal. According to the limit theorem, the Gaussian distribution of the received signal energy is shown in formula (13).

$$Y \sim \begin{cases} N\left(m, 2m\right), & H_0 \\ N\left(2m\left(\lambda+1\right), 2m\left(2\lambda+1\right)\right), & H_1 \end{cases} \tag{13}$$

In formula (13), λ is the instantaneous SNR at the sensing user, $N\left(m, 2m\right)$ is the Gaussian distribution of mean m and variance m. At H_1, $N\left(2m\left(\lambda+1\right), 2m\left(2\lambda+1\right)\right)$ is the Gaussian distribution of mean $2m(\lambda+1)$ and variance $2m\left(2\lambda+1\right)$. The fusion center performs the operation steps of fuzzy integral processing on the collected detection statistics of each perceptual user. After receiving the detection results of each perceptual user, the fusion center performs fuzzy evaluation on the detection results and introduces the consideration of ''uncertainty'' of the perceptual user's detection results information through fuzzy evaluation. According to the preset decision strategy, the fusion center compares the fuzzy integral values of the two fuzzy integrators and makes the final decision, as shown in formula (14).

$$sum_1 = \sum_{i=1}^{n} a_{total1j} \tag{14}$$

In formula (14), $a_{total1j}$ is the fuzzy integral value of the j perceived user signal on the fuzzy integrator H_0, and n is the number of perceived users in the whole system. According to the perceived user signal, the sum of the fuzzy integral values in the absence of the primary user signal is shown in formula (15).

$$sum_0 = \sum_{i=1}^{n} a_{total0j} \tag{15}$$

In formula (15), $a_{total0j}$ is the fuzzy integral value of the j perceived user signal on the fuzzy integrator H_0, and the fusion center compares the value of the sum of the two fuzzy integrals of the fuzzy integrator H_0 and the fuzzy integrator H_1, and then judges the state of the primary user signal according to the sum of the fuzzy integral values corresponding to the fuzzy integrator. When sum_0 is greater than sum_1, the primary user signal is determined as non-existent. On the contrary, the primary user signal exists. Spectrum sensing is one of the important means to achieve wireless communication. Its essence is that agents can continuously optimize their perception and judgment of spectrum usage by using their own behavior and experience feedback values through repeated experiments and learning. In practical applications, spectrum sensing can obtain the specific situation and trend of spectrum use in the current network through continuous detection and analysis, and predict and judge it. These sensing results can provide important data support for subsequent spectrum management and optimization, and help network resources to be used more efficiently. Spectrum sensing can also continuously optimize its sensing strategy and decision-making process through feedback mechanisms and adaptive technology to improve the accuracy and real-time sensing. This can further improve the utilization efficiency of network resources and the quality of user experience, and meet the diverse needs of people for wireless communication. The technologies to reduce the specific use of spectrum resources include spectrum sharing and dynamic allocation, which are shared and allocated according to the actual needs, so that multiple users or systems can share frequency bands and improve the utilization rate of spectrum resources. Dynamic spectrum allocation can be adjusted according to real-time requirements to avoid waste of resources; spectrum perception and cognitive radio can monitor spectrum usage and communicate on idle frequency bands to avoid interference with major users. The cognitive radio system can adjust the frequency to enable unauthorized users to communicate on the unoccupied spectrum; space multiplexing and beam forming, using space multiplexing technology to transmit the signals of the same frequency separately in space to reduce interference. Beamforming technology allows centralized transmission of signals in specific directions, reducing the propagation range of energy, and improving spectrum utilization; more efficient modulation and coding, using more efficient modulation and coding schemes to increase data transmission rates to transmit more data in the same spectrum bandwidth and achieve higher spectrum utilization. Spectrum sensing is an important and developing technology for wireless communication, which has a wide range of application prospects and important research value. With the emergence of new technologies and new application scenarios, spectrum sensing technology will also continue to explore and innovate, bringing greater impetus and development space for future wireless communication. The process of spectrum sensing is shown in Figure 6.

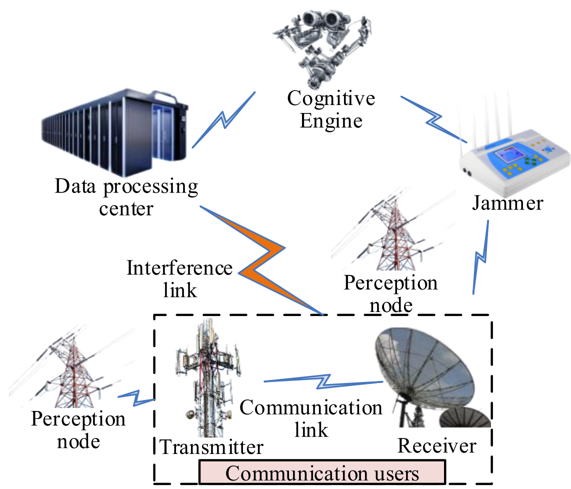

FIGURE 6. Spectral perception process integrating fuzzy integral and multiobjective optimization theory.

In Figure 6, the whole model is mainly composed of communication users and a jamming system. The communication user is composed of a transmitter and receiver, which mainly realizes the transmission and reception of information. The jamming system includes a jammer, cognitive engine, data processing center, and several sensing nodes. The transmitter,

TABLE 1. Parameter settings for each algorithm.

MOPSO	NSGA-II	MOGWO	MOWOA
$c_1 = 2, c_2 = 2$	$d = 22$	ε_1 As the number of iterations increases from linear 2 to 0	The convergence factor a Decreases from 2 to 0 as the number of iterations decreases
$w = [0.1, 0.8]$	$p_1 = 0.75$	Random numbers between the moduli of and [0,1] b_1 b_2	Random numbers between the module of and[0,1] r_1 r_2
$p = 0.45$	$q = \frac{1}{N}$	$T_{\max} = 1000$	$T_{\max} = 1000$
$v = 3.9$	$T_{\max} = 1000$	$M = 100$	$M = 100$
$T_{\max} = 1000$	$M = 100$	\	$p = 0.45$
$M = 100$	\	\	\

jammer, and receiver use USRP RIO software and realize the functions of each part through the programming software on the computer. In order to deal with the problem of channel switching, the working process of the communication jamming system has two parts: spectrum sensing and jamming decision. Specifically, the sensing node and the data processing center realize spectrum sensing, obtain the channel state information, and use the cognitive engine to strengthen learning. After that, the model will learn the channel-switching law between the transmitter and receiver, and make the final interference decision. Combining the whale algorithm and the fuzzy integration algorithm can better handle the uncertainty factors in the multi-objective optimization problem. One possible approach is to initialize a set of solutions that represent different configurations of spectrum resources. The fuzzy integration algorithm is applied to each solution to comprehensively for uncertainty factors. This may involve ambiguous assessment of interference, signal-to-noise ratio, channel quality, and other factors.

IV. SIMULATION EXPERIMENT SETUP AND RESULT ANALYSIS

A. SPECTRUM SENSING ALGORITHM ANALYSIS BASED ON MULTI-OBJECTIVE OPTIMIZATION PRINCIPLE

This paper studies how to improve the throughput of secondary users and reduce interference to primary users in cognitive wireless networks. An efficient network scheduling algorithm is designed to reasonably allocate the available spectrum resources in the network. This algorithm must take into account the requirements of both primary and secondary users to achieve a balance between the interference of primary users and the throughput of secondary users. The improved whale optimization algorithm is qualitatively analyzed by using the measurement indicators, i.e. IGD, and spacing. The spectrum sensing scheme used in this chapter is simulated in MATLAB. Each simulation runs 35 times, and each iteration is 1300 times. The number of samples detected is considered to be 130, and noise and sensing variance are generated randomly. Model parameter settings are shown in Table 1.

In Table 1, MOPSO's learning factors are c_1 and c_1, w is weight, p is mutation probability, and v is parameter selected for leaders; In NSGA-II, d is the binary cross-distribution index, p_1 is the cross probability, q is the mutation rate, N is the chromosome length; In MOGWO, a is the convergence factor, and the random vectors are b_1 and b_2; In MOWOA, the random vectors are r_1 and r_2, p is the probability of spiral update mechanism, $T_{\max}$ is the maximum number of iterations, and M is the population size. Then, MOWOA, MOGWO, MOPSO, and NSGA-II are compared, and the Pareto frontiers of the four algorithms are compared. The throughput and Pareto frontiers are shown in Figure 7.0

In Figure 7, by analyzing the algorithms such as MOWOA, MOGWO, MOPSO, and NSGA-II, the approximation between the Pareto front obtained and the actual Pareto front is compared. This method has better optimality. For multi-objective optimization problems, the proposed method has a fast convergence speed, fast convergence speed, and independent of local extremum. According to the analysis results of the inverse generational distance (IGD), the convergence curve of throughput can be analyzed, as shown in Figure 8.

The processing capacity shown in Figure 8 (a) gradually reaches the maximum processing capacity of 16.8 after 600 cycles, and then continues to decrease. The same is true of the processing capacity 17.4 shown in Figure 8 (b), and the same is true of the processing capacity 17.4 after 600 cycles. Figure 8 (d) shows the maximum throughput after 1000 replicates, i.e. 10.8. In Figure 8 (d), the maximum throughput is 14.1 after 400 replicates. Compared with the other two methods, this method can achieve 9.2% network throughput and effectively improve network performance. According to the throughput calculation after iteration, the interference convergence curve of the algorithm can be measured, as shown in Figure 9.

In Figure 9, the proposed multi-objective optimization method based on Bayesian converges to the minimum value when the iteration number increases, which reduces the impact on the main users, and maintains the stability of the system when the iteration number increases, thus

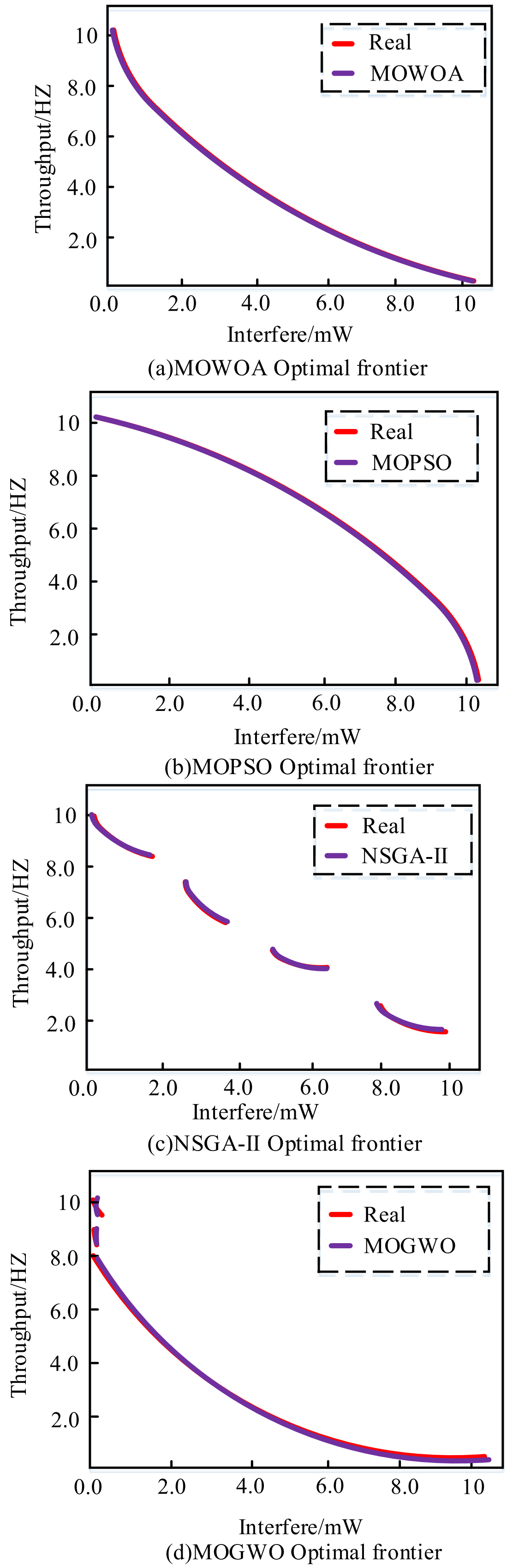

FIGURE 7. Comparison of throughput and interference Pareto frontiers of different algorithms.

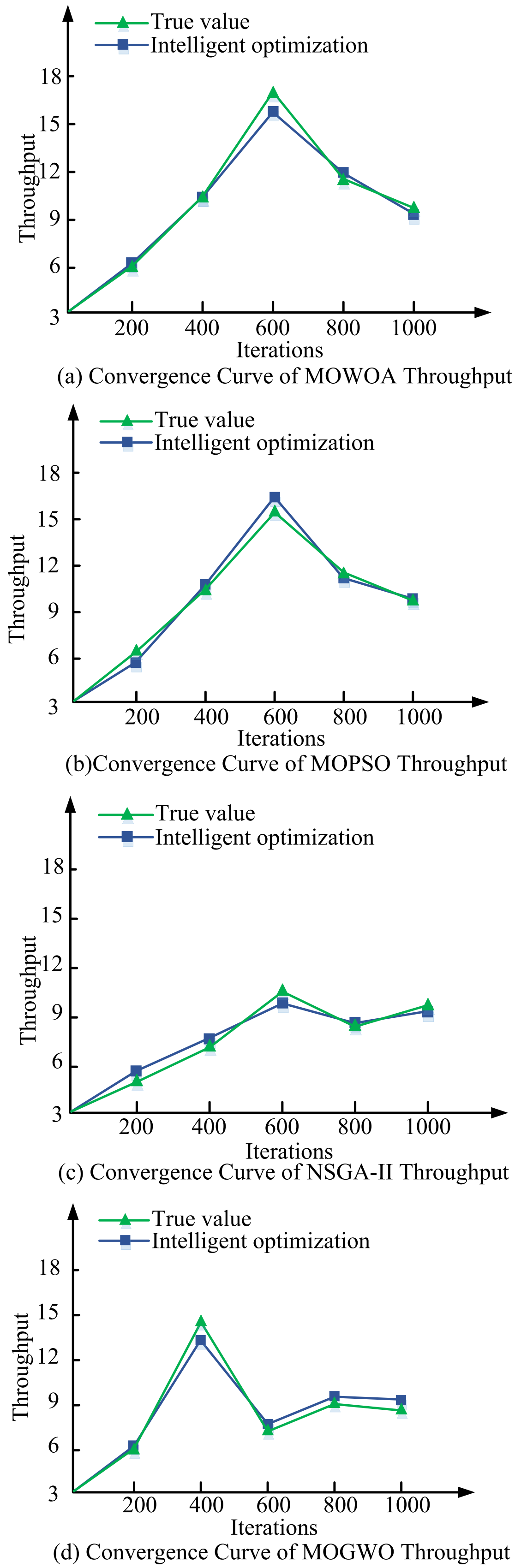

FIGURE 8. Throughout convergence curves of different algorithms.

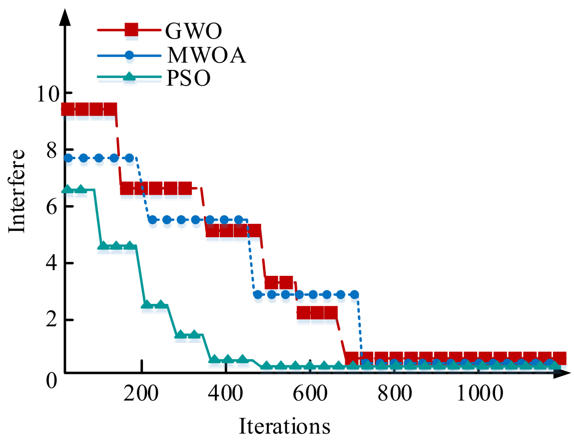

FIGURE 9. Interaction convergence curve.

improving the overall performance of cognitive wireless networks. Figure 10 shows the evaluation efficiency of different network sizes.

In Figure 10, the detection probability of the Mo particle swarm optimization algorithm decreases as the cognitive wireless network scale increases, while the detection probability of MOWOA algorithm remains unchanged, so as to maximize the detection probability.

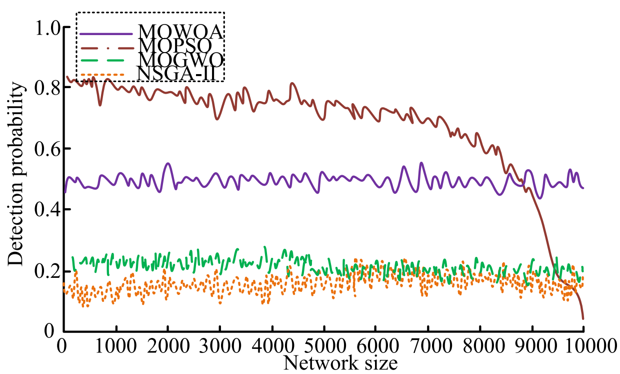

FIGURE 10. Evaluation efficiency of different network sizes.

B. SPECTRUM SENSING TRAINING AND ANALYSIS BASED ON FUZZY INTEGRAL AND MULTI-OBJECTIVE OPTIMIZATION THEORY

In the realm of wireless communication systems, spectrum resources stand as both precious and scarce commodities. Effectively utilizing and efficiently managing this limited resource necessitates the implementation of robust spectrum sensing and processing techniques. Within wireless communication, the strategic utilization and management of spectrum resources across the network represent a crucial concern, profoundly impacting the network's overall performance and efficiency. In the context of the rapidly evolving network services landscape, spectrum resources have transcended their exclusive association with individual users or single access points, transitioning into a realm of increasingly rare assets. This paradigm shift underscores the urgency of finding effective solutions to optimize spectrum resource utilization within wireless networks. The relationship between Signal-to-Noise Ratio (SNR), detection probability, and false alarm rate is elegantly depicted in Figure 11, providing valuable insights into the complex interplay of performance factors in this domain.

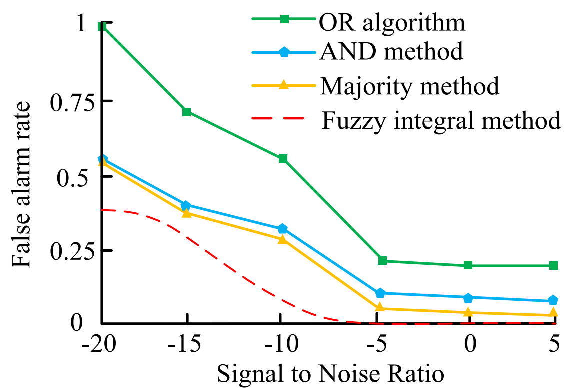

FIGURE 11. False alarm rate graphs for variable fusion methods.

In Figure 11, this project proposes a PU signal detection algorithm, which will minimize the false positive probability of the PU signal detection algorithm, but has the maximum false positive probability. The fuzzy integral method has the minimum false alarm rate. It is proposed to use different mobile terminals and mobile terminals for different types of mobile terminals. For various interference modes such as random interference and multi-tone interference, the method of combining multi-objective optimization and fuzzy integral is used to compare and analyze the interference probability under different interference modes. Mono interference refers to the noise generated by a single disturbance source, multi-channel interference refers to the noise generated by multiple disturbance sources at the same time, and random interference refers to uncertain noise. Further, the effective interference rate is calculated under different interference modes, as shown in Figure 12.

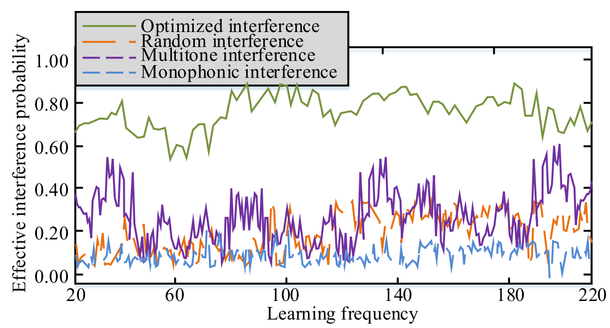

FIGURE 12. Effective interference probability of different interference modes.

In Figure 12, with the increase in learning times of the system, the effective interference probability under the

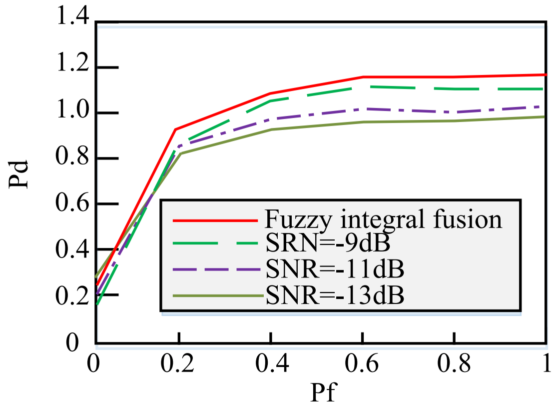

FIGURE 13. Comparison of fuzzy integral fusion and detection probability of each CU with different SNR values.

optimized spectrum sensing still shows a continuous growth trend. When the number of learning reaches 100, the effective interference probability under the optimized spectrum sensing fluctuates at 0.79 without much change. In addition, in the case of random, single-tone, and multi-tone interference, the effective interference rate does not change much with the learning of the system. Among them, the random interference is stable at about 0.1, the single-tone interference is stable at about 0.3, and the multi-tone interference is basically stable at about 0.4. It is assumed that the SNR values are −9db, −11db, −13db respectively. When the SNR value of CU is different, the comparison between the fuzzy integral fusion and the detection probability of each CU is shown in Figure 13.

In Figure 13, as the SNR value increases, the spectrum sensing performance of a single CU will also increase, and the spectrum sensing performance of the cooperative spectrum sensing algorithm using fuzzy integral is better than that of a single CU. The cooperative sensing method using fuzzy integration is better than the single-machine system. On this basis, it is proposed and applied to the actual system. This also shows that the proposed method is an effective cooperative spectrum sensing method.

V. CONCLUSION

By comprehensively considering multiple factors, such as spectrum throughput, interference effect, etc., the performance of the communication system can be ensured and the utilization of spectrum resources is improved while using as few spectrum resources as possible. The algorithm not only uses the whale algorithm but also combines the fuzzy integral algorithm to comprehensively evaluate the uncertainty factors, so as to obtain the optimal spectrum resource allocation scheme. Results showed that system throughput was 14.1 after 400 cycles according to the calculation results of IGD; After 600 cycles, the throughput of MOPSO reached 17.4. The proposed multi-objective optimization method based on Bayes converged to the minimum value when the iteration number increased, which reduced the impact on the main users, and maintained the stability of the system when the iteration number increased, so as to improve the overall performance of cognitive wireless networks. The detection probability of the Mo particle swarm optimization algorithm decreased as the network scale increased, while the detection probability of the MOWOA algorithm remained unchanged, so as to maximize the detection probability. The random interference was stable within 0.1, the single-tone interference was within 0.3, and the multi-tone interference was within 0.4. Combining multi-objective optimization with fuzzy integral, a spectrum sensing method with strong scalability, practicability, and applicability was proposed, which can provide a new idea for spectrum resource management in wireless communication systems. According to the test data, this paper has done some preliminary analysis and processing, but further analysis and research are still needed to improve the accuracy and reliability of the test results. Preliminary analysis and processing of experimental data have been conducted, but further research is still required to enhance the precision and reliability of the results. Moreover, combining this method with other approaches holds promise for achieving better performance. This integration presents a prospective direction for real-world applications. In future research, it can be better developed in practical application by combining it with other methods.

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