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Anti-interference Technology of Intelligent Communication Based on Improved GA and GWO

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Abstract

Chaotic mapping enhances anti-interference in frequency hopping communication by optimizing genetic algorithm population initialization. An intelligent decision engine model employs optimized grey wolf parameters and individual exchange mechanisms, enhancing grey wolf optimization convergence speed for constructing frequency hopping patterns. Experimental data reveals the improved genetic algorithm's efficiency with average run times of 0.312s and 0.057s for adaptive and enhanced versions, respectively. Achieving optimal solution convergence rates of 99.3% and 100%, the enhanced algorithm boosts decision-making accuracy and efficiency. The intelligent decision engine exhibits strong anti-interference capabilities, suitable for −2dB to 10dB signal-to-interference ratios with error rates below 10^{-6}. The improved grey wolf optimization algorithm surpasses traditional approaches, yielding a 9.5% profit increment with a total value of 2310. This technology showcases adept learning and anti-interference capabilities, offering innovative solutions for communication systems and anti-interference technology advancements.

Keywords

communication system, anti-interference, improved GA, improved GWO, fitness, error rate

1 Introduction

In the rapid advancement of modern communication technology, communication anti-interference technology has exerted a crucial function in ensuring communication quality. In communication systems, anti-interference technology can effectively improve the reliability and stability, thereby ensuring the normal operation of the communication system [1]. The anti-interference phenomenon mainly occurs during wireless communication, where the enemy attempts to interfere with our communication through various means. This phenomenon has significant value in military, security, and civilian fields, and research on anti-interference technology can improve the stability and reliability of communication systems. Interference in communication signals can lead to a decrease in signal quality, an increase in bit error rate, and even possible communication interruption. This will have a serious impact on key areas such as command, combat, and rescue. To solve this problem, researchers have proposed various anti-interference techniques, including adaptive filtering, encoding and decoding, intelligent algorithms, etc. These technologies achieve effective suppression of interference by monitoring and analyzing interference signals in real-time, adaptively adjusting communication parameters. On the other hand, using encoding technology to improve the anti-interference ability of signals enables communication systems to maintain stable operation even in harsh environments. In addition, intelligent algorithms such as neural networks and genetic algorithms have also achieved significant results in the field of anti-interference. Through these solutions, communication systems can automatically adjust in the face of interference, improve anti-interference capabilities, and ensure security and stability in critical areas. At present, anti-interference technology mainly includes two types: active anti-interference technology and passive anti-interference technology. Active anti-interference technology analyzes interference signals and uses corresponding algorithms to eliminate interference [2]. Passive anti-interference technology, on the other hand, eliminates the impact of interference on communication systems by detecting and analyzing interfering signals. The existing active anti-interference technologies mainly include blind hole algorithms based on traditional filters and improved anti-interference technologies based on

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Genetic Algorithm (GA) [3]. Although these technologies can improve the anti-interference of communication systems to a certain extent, their anti-interference is not ideal in complex scenarios, and some anti-interference algorithms have high complexity and poor computational efficiency [4, 5]. In addition, anti-interference algorithms need to be adjusted and optimized according to specific communication systems and scenarios to achieve the best anti-interference effect.

GA and Grey Wolf Optimization (GWO) algorithms are both classic optimization algorithms with good global search capabilities and competitive strategies, which can effectively solve some complex problems. In the field of intelligent communication anti-interference technology research, there are many parallel methods to choose from besides GA and GWO. For example, particle swarm optimization algorithm (PSO), cuckoo search algorithm (CSA), simulated annealing algorithm (SA), and bat algorithm (BA). These algorithms have their own advantages in solving communication anti-interference problems, can solve complex optimization problems, and improve the performance of communication systems. Both GA and GWO methods are classic optimization algorithms with good global search and competition strategies, capable of handling complex problems. In the field of intelligent communication anti-interference, although there are multiple parallel algorithms to choose from, each with its own advantages, the uniqueness of GA and GWO algorithms makes it possible to break through the limitations of existing active anti-interference technologies in complex scenarios when dealing with communication anti-interference, providing the possibility of achieving better anti-interference effects.

GA and GWO have been widely applied in industries, construction, communication, and computer fields. Kumar et al. used intelligent technology and GA to model and optimize the spark discharge process, demonstrating its effectiveness in predicting the output quality characteristics of input machining parameters. The designed method improved the machining performance of alloy precision drilling processes [6]. Liu et al. used the GA to analyze and optimize pipelines, successfully reducing pipeline warping. Through computational fluid dynamics analysis, they found that the rear guide plate had a positive impact on aerodynamic performance, providing an innovative solution for the design and performance optimization of pipeline fans [7]. Chen et al. proposed a model combining adaptive GA and modified Newton method [8] for system identification of building structures. The experimental results showed that this controller had robustness to changes in system parameters, providing a new method for using active mass dampers to control nonlinear structures, especially high-rise buildings under seismic excitation. Bai et al. used the cuckoo search GWO algorithm to identify variables in solid oxide fuel cells and modeled them for various temperatures and pressures. It outperformed other optimization algorithms in accuracy, robustness, and convergence speed. For an operating pressure of 1 atmospheric pressure, the error value was 1.3% [9]. Mahmoud et al. applied a novel hybrid azalea search strategy and GWO technique to design the controller parameters installed in voltage source converters in offshore wind farms. The method outweighed traditional strategies in optimization performance, especially in symmetric and asymmetric faults [10].

To improve the performance of communication systems, Du et al. used orthogonal frequency division multiplexing radar for distributed target detection in mixed environments. A generalized likelihood ratio test detector based on expectation maximization was developed. The built detector had superior performance compared with the ideal generalized likelihood ratio test detector [11]. Yang et al. used intelligent reflective surfaces to improve anti-interference communication performance. A joint optimization problem for base station power allocation and reflection beamforming was proposed. They used fuzzy winning or learning fast strategy mountain climbing learning methods to jointly optimize anti-interference power allocation and reflection beamforming strategies. This method could effectively optimize the speed and transmission protection level of auxiliary systems [12]. Sharma et al. explored the application of intelligent reflective surface technology in reducing self interference effects in full duplex radio frequency wireless communication systems. By studying the interruption probability and average sign error probability, a closed form expression was obtained. The research results showed that intelligent reflective surface technology could effectively reduce self interference in full duplex communication systems [13]. Li et al. introduced anti-interference tolerance to measure the reliability performance of cognitive frequency hopping systems. By analyzing the effects of false alarm probability, an analytical expression for anti-interference tolerance was derived. The results verified the effectiveness of these analyses and pointed out that parameters could be flexibly adjusted based on theoretical deduction to meet various communication scenarios [14]. Mu et al. proposed an intelligent spectrum allocation scheme ground on machine learning for co-requency interference between coexisting wireless area networks. Combining graph coloring and partitioning ideas, self-organizing dynamic clustering and frequency band coordination were achieved. The results showed that this method could adapt well to rapidly changing wireless body area networks in topology, and significantly improve the anti-interference performance, and system stability [15].

In summary, many researchers have conducted different researches and designs on communication anti-interference. However, the above research still has drawbacks such as complex optimization algorithms and models, high computational and implementation costs. Therefore, the study proposes an intelligent communication anti-interference technology based on improved GA and GWO, aiming to effectively improve the anti-interference ability and computational efficiency of communication systems. GA, as an adaptive search algorithm, has good global search capability and can maintain population diversity during the search process, thereby improving anti-interference performance. GWO is a heuristic optimization algorithm based on grey wolf hunting behavior, which has fast convergence speed and strong local search ability, and can effectively solve communication anti-interference problems. Simultaneously choosing these two algorithms for research can fully utilize their advantages and achieve more efficient and accurate communication anti-interference optimization. By improving the GA and GWO algorithms, their performance can be further enhanced, enabling communication systems to maintain high anti-interference capabilities and system performance even in complex interference environments.

2 Methods and materials

2.1 Intelligent decision-making method based on improved GA

With the rapid development of wireless communication technology, wireless communication systems face many security threats and interference challenges in complex environments. To optimize the anti-interference ability of wireless frequency hopping communication systems in complex electromagnetic environments, an intelligent frequency hopping decision engine based on an improved GA is proposed. The randomness in chaotic systems is used to improve the population initialization operation of GA. An improved Logistic-Fibonacc cascaded chaotic map is used to generate sequences to replace the traditional random initialization method. The mathematical formula for logistic chaotic mapping is shown in Eq. (1).

$$s_{\text{chaos}\_i+1} = \mu s_{\text{chaos}\_i}(1 - s_{\text{chaos}\_i}) \tag{1}$$

In Eq. (1), the mapped data is S_{chaos_i+1} and the control parameter is μ. The generalized third-order Fibonacci mathematical formula is shown in Eq. (2).

$$s_{LF\_i} = (Q_1 s_{LF\_i-1} + Q_2 s_{LF\_i-2} + Q_3 s_{LF\_i-3}) \bmod Q_4 \tag{2}$$

In Eq. (2), the parameter after third-order processing is S_{LF_i}. The constant is Q. The residual operation is mod. The new generalized third-order Fibonacci formula obtained by Logistic-Fibonacci cascade is shown in Eq. (3).

$$s_{LF\_i} = \begin{pmatrix} s_{\text{chaos}\_3i-1} s_{LF\_i-1} \\ + s_{\text{chaos}\_3i-2} s_{LF\_i-2} \\ + s_{\text{chaos}\_3i-3} s_{LF\_i-3} \end{pmatrix} \bmod Q_4 \tag{3}$$

In Eq. (3), the value range of the chaotic sequence is [0,1]. The initialization results of population individuals obtained from chaotic sequences are shown in Eq. (4).

$$X = X_{\min} + (X_{\max} - X_{\min}) \cdot s_{LF} \tag{4}$$

In Eq. (4), the individual initialization vector is X. The minimum of the solution vector is $X_{\min}$. The maximum of the solution vector is $X_{\max}$. The chaotic sequence vector is S_{LF}. Chaotic sequence is used to replace random initialization to avoid the population aggregation, so that the population individuals are evenly distributed in the whole feasible region to accelerate the convergence speed of the algorithm, and help to avoid over fitting phenomenon. Adaptive GA is a GA that optimizes the evolution process. Its main difference is the selection operation. There is a linear relationship between the probability of individual selection and its fitness value, which leads to the evolution direction of the population biased towards local optimum, and thus falls into local optimum [16]. To solve this problem, when selecting individuals, researchers should select individuals with excellent performance and ensure population diversity to avoid the local optimization. The chromosome similarity is displayed in Eq. (5).

$$\zeta(X_i, X_j) = \begin{cases} 1, \left|\xi(X_i) - \xi(X_j)\right| \le \varepsilon \\ \quad 0, \quad \text{others} \end{cases} \tag{5}$$

In formula (5), the individual chromosomes are X_i and X_j respectively. The chromosome fitness value is ξ. The threshold of chromosome similarity is ε. The threshold combined with fitness is shown in Eq. (6).

$$\varepsilon = \frac{\max(\xi) - \min(\xi)}{N_{toa}} \tag{6}$$

In Eq. (6), the minimum value of fitness in the population is min(ξ) and the maximum value is max(ξ). The population size is N_{toa}. The final selection operator is shown in Eq. (7).

$$K(X_i) = \phi\xi(X_i) + \frac{(1-\phi)}{\sum_{k=1}^{N_{toa}} \zeta(X_i, X_j) \sum_{k=1}^{N_{toa}} \zeta(X_k, X_j)} \tag{7}$$

In Eq. (7), the result of the selection operator is $K(X_i)$. The selected number of operations is k. The weighting factor is ϕ. In the late stage of adaptive GA, the efficiency is prone to become low. The study uses the genes with higher fitness in the population for crossover operation. The crossover calculation process is shown in Eq. (8).

$$X_{son} = \begin{cases} rX_i + (1-r)X_{st}, & \xi(X_i) > \xi(X) \\ rX + (1-r)X_{st}, & \text{others} \end{cases} \tag{8}$$

In Eq. (8), the offspring after parent crossover is X_{son}. The parent randomly selected from the population is X_i. X_{st} is the strongest parent. The random vector is r. The study uses a non random strategy to select the elite solution that wins in the competition to cross with the individuals that perform well in the population. The population information is comprehensively utilized to increase the diversity of offspring, which helps to optimize the efficiency and convergence speed of the crossover operator to produce excellent offspring. In the mutation, aimless blind random mutation is no longer carried out, but the effective information of some excellent individuals in the current population is used as guidance [17]. In addition, considering that changing only one gene may not have obvious effect on the improvement of fitness, mutation operations are carried out at multiple loci in the chromosome to increase the direction of variation. The first form of mutation operation is shown in Eq. (9).

$$X'_{i,j} = X_{pbest,j} + \alpha(X_{i,j} - X_{k,j}) \tag{9}$$

In Eq. (9), the j-group gene of individual i is $X_{i,j}$. The gene obtained after mutation operation is $X_{i,j}$. The j-group gene of individual *pbest* in the excellent population is $X_{pbest,j}$. The j-group gene of randomly selected individual k is $X_{k,j}$. The random real number is α. The second form of mutation operation is shown in Eq. (10).

$$X'_{i,j} = X_{best,j} + \alpha(X_{i,j} - X_{i,j}) \tag{10}$$

In Eq. (10), the j-group gene of the optimal individual in the current population is $X_{pbest,j}$. The adaptive proportion parameter plans the individual proportion of mutation operation, and the calculation is shown in Eq. (11).

$$\eta = \begin{cases} 0.5, & \Delta ad_1 + \Delta ad_2 = 0 \\ 0.2 + 0.6\dfrac{\Delta ad_1}{\Delta ad_1 + \Delta ad_2}, & \text{others} \end{cases} \tag{11}$$

In Eq. (11), the adaptive proportional parameter is η. The average fitness growth of the two variation modes is $\Delta ad1$ and $\Delta ad2$, respectively. Chaotic perturbations are used to shorten the probability of local optimal solution, as shown in Eq. (12).

$$X' = X + (X_{\max} - X_{\min}) \cdot \sin(2\pi s_{\text{chaos}}) \tag{12}$$

In Eq. (12), the individual after chaotic disturbance is X'. The local optimal individual is X. The chaotic disturbance vector is S_{chaos}. The time complexity S_{chaos} of the improved GA is shown in Eq. (13).

$$O_{GA} = o(N_{tol}N_{len}) + o(N_{\max}(N_{tol} + N_{tol}N_{len})) \tag{13}$$

In Eq. (13), the chromosome length is N_{len}. The maximum iteration is $N_{\max}$. The time complexity of chaotic sequence, original population generation, selection operator and crossover mutation operation is $o(N_{tol}N_{len})$. In summary, the study improved the population initialization operation of GA algorithm by utilizing the randomness in chaotic systems, resulting in a uniform distribution of population individuals within the feasible domain, thereby accelerating the convergence speed of the algorithm. At the same time, to avoid falling into local optima, the study introduced chromosome similarity functions and adaptive GA in the selection operation to ensure population diversity. In addition, the study also employed various strategies to optimize crossover and mutation operations, improving the algorithm's global search capability. Intelligent decision engine is a key component of frequency hopping communication system. Based on interference identification, it can find the optimal solution that can meet the decision goal and output it by improving GA according to the external environment such as interference type and interference power, as well as the constraints and expected goals of the communication system, so as to realize the intelligent adjustment of modulation mode, transmission power and frequency hopping pattern of frequency hopping communication system and improve the anti-interference performance [18]. The intelligent decision engine model is built as shown in Fig. 1.

In the intelligent decision engine model, the interference information is represented as a vector, which contains the external environment information such as interference type and interference power. At the same time, the

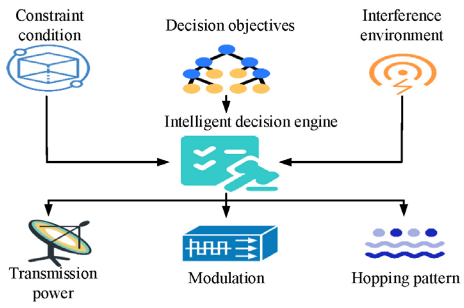


Fig. 1 Intelligent decision engine model construction

vector contains the target of frequency hopping communication system, modulation mode, transmission power and so on. The intelligent decision engine outputs an optimal solution vector by taking the interference information and the expected target vector as input, which represents the modulation mode, transmission power and other decisions that the frequency hopping communication system should adopt in the current interference environment. The objective function of the decision engine is shown in Eq. (14).

$$\vartheta = \omega_1 \beta_{err} + \omega_2 \beta_{rat} + \omega_3 \beta_{tp} + \omega_4 \beta_{fh} \tag{14}$$

In Eq. (14), the objective function of the decision engine is ϑ. The normalized bit error rate β_{err}, transmission efficiency β_{rat}, transmission power β_{tp} and frequency modulation gain β_{fh} correspond to the weights ω_1, ω_2, ω_3 and ω_4. The intelligent engine decision-making process is shown in Fig. 2, including two steps: interference identification and objective function input. Firstly, the interference recognition results and the objective function are input to the intelligent decision engine. Then, the maximum iterations and the initialization population are set. In the iteration process, the intelligent decision engine performs the selection operation and selects the individuals with better fitness for the next iteration according to the current population state. The current population is crossed to generate new offspring. The current population is mutated. Through mutation operation, new genetic variation can be introduced to increase the adaptability of the population [19]. At the same time, the chromosome that meets the disturbance condition is disturbed by chaos to increase its randomness and complexity. During the iteration process, the intelligent decision engine will determine whether the maximum iteration is reached. If not, it will return to select. Otherwise, it will proceed to the next step. Finally, according to the optimal chromosome information, the transmit power, modulation mode and frequency hopping pattern are calculated and output as the decision result.

2.2 Anti-interference frequency hopping sequence design method based on improved GWO

To use the interference information provided by spectrum sensing technology, an optimized GWO is built to achieve a more flexible anti-interference method. GWO is inspired by the hunting behavior of gray wolf packs, where there are levels of leader, secondary leader, executor, and regular wolf in the pack. The algorithm initializes a group of gray wolves randomly distributed in the search space. During the hunting process, the wolf leads the pack, the secondary leader and executor wolves assist, and the regular wolf follows. When updating the position, first calculate the optimal position estimate of the prey, and then update the position of the wolf. The convergence factor decreases linearly from 2 to 0. The size of the wolf pack determines the number of individuals involved in optimization, depending on the complexity of the problem and the size of the search space. The maximum number of iterations controls the termination of the algorithm, and the convergence factor affects the algorithm's exploration and development capabilities. Early exploration is helpful for extensive exploration, while later exploration is beneficial for fine search. The improved GWO algorithm achieves more efficient search capability and convergence speed through non-linear control parameters and individual information exchange mechanism. In the design of

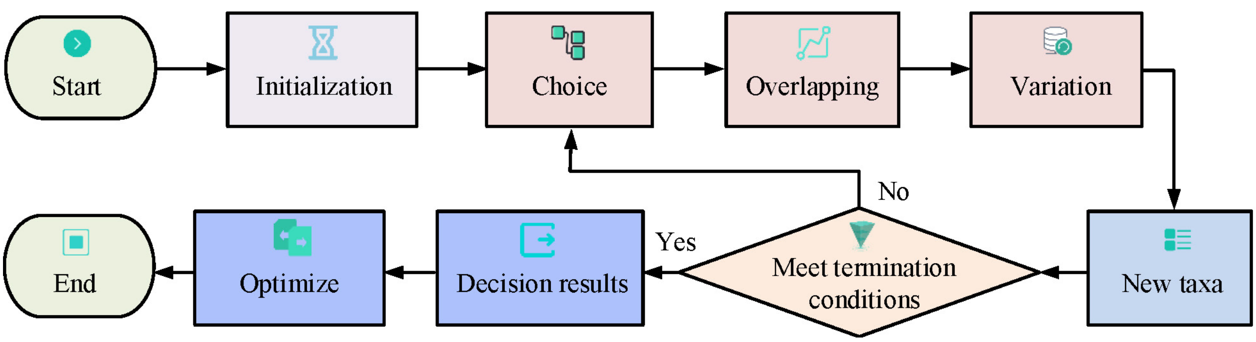


Fig. 2 The decision-making process of the intelligent engine

anti-interference frequency hopping sequences, this algorithm optimizes the performance indicators of frequency hopping sequences, including reducing the probability of signal interception and interference, improving frequency hopping gain, and achieving a more uniform frequency distribution. In the actual communication system, the quality of frequency hopping sequence will directly affect its anti-interference ability. The construction process of anti-interference frequency hopping sequence is shown in Fig. 3. The traditional frequency hopping sequence has strong anti-interception ability, but the influence of blocking interference is not considered. Therefore, it is necessary to ensure a low probability of interception while avoiding blocking interference. The performance evaluation standard of frequency hopping sequence is Hamming autocorrelation, which represents the number of frequency collisions of frequency hopping sequence in a period with a certain delay. If the Hamming autocorrelation value is small, it indicates that the frequency coincidence times are less in a cycle, and the frequency collision probability is smaller. To reduce the probability of signal interception and interference, the frequency hopping sequence should have a wide spectrum range, that is, it has a high frequency hopping gain [20, 21]. At the same time, its uniformity is also an important performance index. The value close to 0 indicates that the frequency points are more evenly distributed in a cycle, and the uniformity of frequency hopping sequence is better. When evaluating the frequency hopping sequence, the following four performance indicators need to be considered: the probability that the frequency hopping signal is interfered under the current interference, the maximum Hamming autocorrelation value, the wide spectrum range that the frequency hopping signal should have, and the uniformity.

The anti-interference frequency hopping sequence is optimized by using the improved GWO. To improve the search ability of GWO, the gray wolf attraction control parameters need to be optimized. The nonlinear variable control parameters are used, as shown in Eq. (15).

$$\chi = \frac{2}{1+\exp\{\chi_1[\chi_2-(n/N_{tol1})]\}} \tag{15}$$

In Eq. (15), the control parameter is χ. The current iteration is n. The maximum iteration is N_{tol1}. The initial control parameters are N_{tol1} and χ_2, respectively. Reverse learning strategy is an adaptive adjustment strategy that simulates the elimination mechanism of inferior solutions in nature, guiding algorithms to evolve towards high-quality solutions and improving solving efficiency. To enhance the convergence speed of GWO, the first reverse learning strategy is improved, as shown in Eq. (16).

$$G' = G^0 + \varpi\left(\frac{(G_{\max}+G_{\min})}{2} - G^0\right) \tag{16}$$

In Eq. (16), the reverse solution of the improved reverse learning is G'. The reverse solution of traditional reverse learning is G^0. The minimum and maximum values in the solution region are $G_{\min}$ and $G_{\max}$, respectively. The uniform random variable is ϖ. In the standard algorithm, the individuals in the wolf pack are always led by the top three wolves. If the gray wolf of the current leadership is located in the local optimal solution region, it will make the whole wolf group close to the local optimal solution region, so that it will eventually converge to the local optimal solution. In this process, there is no information exchange among other individuals in the wolf pack, and the information utilization rate can be further improved. Therefore, the study proposes an individual information exchange mechanism, as shown in Eq. (17). The individual information exchange mechanism is a method of transmitting beneficial information within a group, enabling the entire group to quickly find high-quality solutions in the search space through information exchange between individuals.

$$G_i^{\text{next}} = G_i + r_{\text{levy}}(\iota)\cdot(G_{\text{best}} - e\cdot(G_i+G_k)) \tag{17}$$

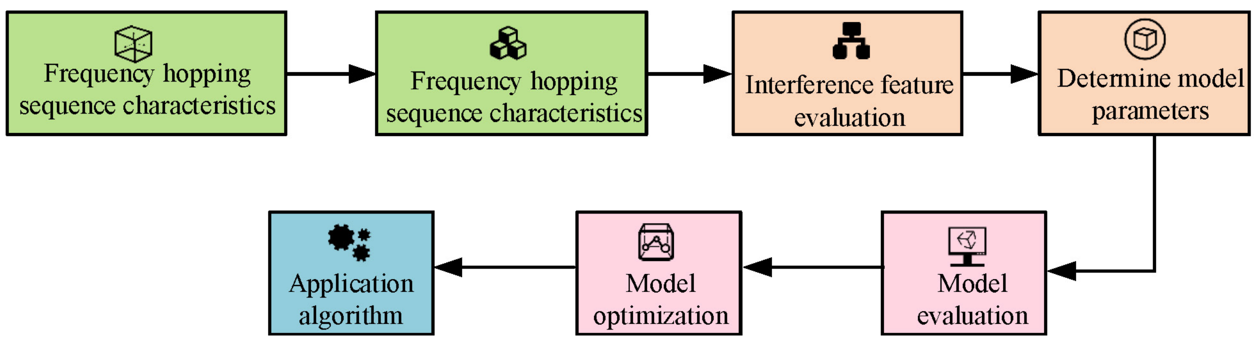


Fig. 3 The construction process of the anti-interference frequency hopping sequence

In Eq. (17), the i-th gray wolf in the wolf pack is G_i. The k-th gray wolf selected is G_k. The communication between the two is G_i^{next}. The best gray wolf is G_{best}. The random vector is e. The random vector obeying Levy distribution is $r_{\text{levy}}(t)$. Levy flight simulates insects searching globally through random walks and sudden jumps during the foraging process, in order to find the optimal solution over a large area and improve solving efficiency. The time complexity O_{GWO} of the improved GWO algorithm is shown in Eq. (18).

$$O_{GWO} = o(N_{tol1} N_{len1}) + o(N_{\max 1}(N_{tol1} N_{len1})) \tag{18}$$

In Eq. (18), the grey wolf individual vector dimension is N_{len1}. The maximum iteration is $N_{\max 1}$. The initialization time complexity is $o(N_{tol1} N_{len1})$. The time complexity of location update, reverse learning and gray wolf individual communication is $o(N_{tol1} N_{len1})$. The anti-interference sequence construction process based on the improved GWO is shown in Fig. 4.

The anti-interference sequence construction process based on the improved GWO is as follows. Firstly, the frequency hopping sequence length, the frequency points and the time spectrum of interference signal are determined. The above parameters are used as the input of the algorithm. Then, the algorithm parameters, the gray wolf populations, and the maximum iterations are initialized. After initializing the wolf pack, each gray wolf individual represents a different frequency hopping sequence. The fitness of each gray wolf is calculated and the update parameters are determined. After completing the position update of the gray wolf population guided by the leadership, the reverse learning strategy is implemented to retain the gray wolf position. In the information exchange between gray wolf individuals, Eq. (17) is applied to complete the information exchange. The gray wolf populations before and after information exchange are merged and compared, and the gray wolf individuals with strong fitness are retained. Whether the number of iterations meets the maximum iteration is judged. If it meets the requirement, the optimal gray wolf individual will be output. Otherwise, the update parameter will be returned. Finally, according to the optimization results obtained by GWO algorithm, the frequency hopping pattern is constructed.

In summary, the study improved the search ability and convergence speed of the GWO algorithm by nonlinearly changing the attraction control parameters of grey wolves and introducing an individual information exchange mechanism. In addition, the study also considered the uniformity of frequency hopping sequences to reduce the probability of signal interception and interference. Through this method, the study overcomes some known drawbacks of the GWO algorithm, including local optimal solution problems and slow convergence speed, thereby achieving more effective anti-interference communication.

3 Results

3.1 Application analysis of intelligent decision method

The experiment is tested on a real hardware platform using python programming language. The hardware configuration includes: Intel Core i7-9750H @ 2.60GHz for CPU, NVIDIA GeForce GTX 1650 Super for GPU, 8GB DDR4-3200MHz for memory, 1TB NVMe solid state hard disk, and windows 10 for operating system. The experiment uses Turbo code to encode the frequency hopping communication system. The code rate is 1/3 and the hop speed is 10k hop/s. The effect of different parameters on algorithm performance is shown in Fig. 5.

In Fig. 5(a), the weighting coefficient is 0.5, and the control parameters are 2.0, 3.5 and 4.0 respectively. When the

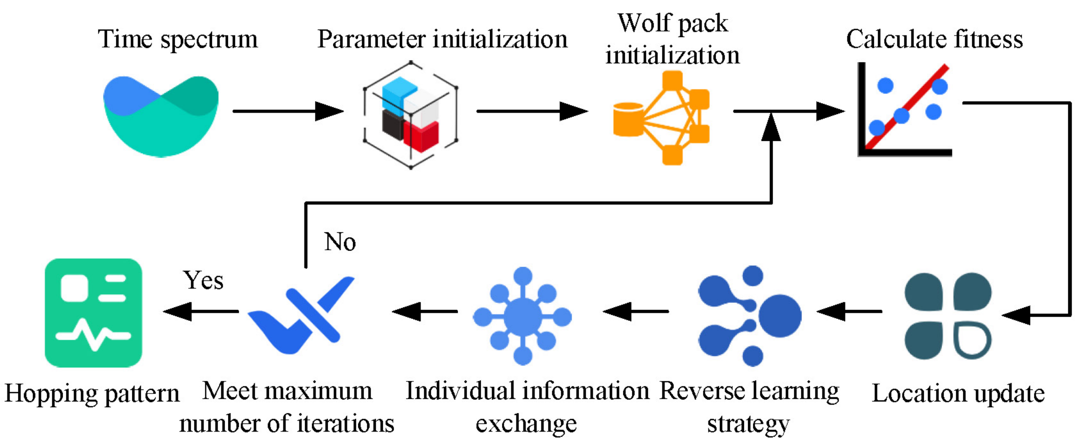
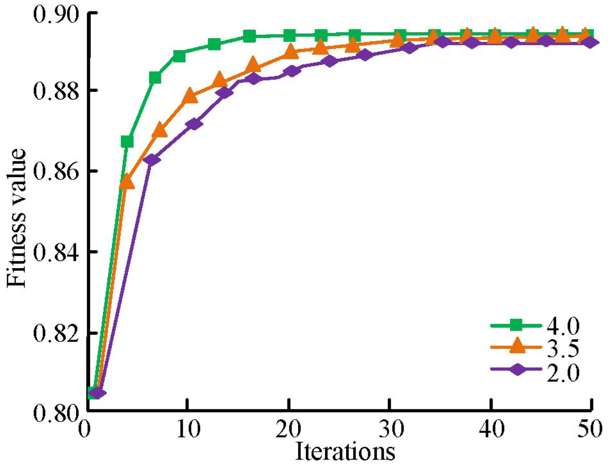


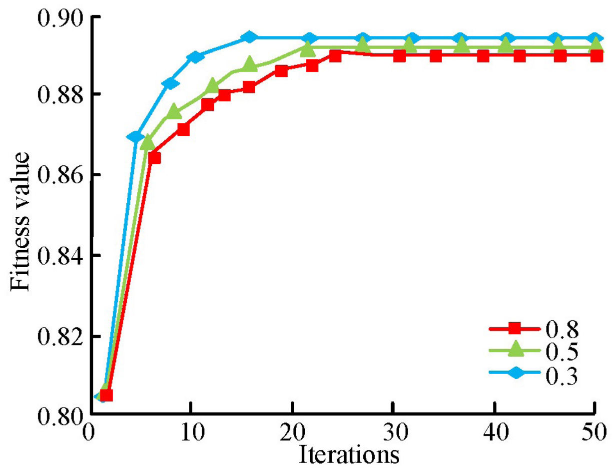
Fig. 4 Construction process of anti-interference sequence based on the improved GWO

control parameter was 4, the population fitness increased faster and the distribution was more uniform. In Fig. 5(b), the control parameter is 4, and the weighting parameter is 0.3, 0.5 and 0.8 respectively. When the weighted parameter value was 0.3, the population fitness increased faster. Therefore, the control parameter of the algorithm is set to 4.0 and the weighting coefficient is set to 0.3. To study the performance of the improved GA, the adaptive GA is compared in the experiment. The fitness iteration of different algorithms is shown in Fig. 6.

Fig. 6(a) displays the fitness iteration of the improved GA, and Fig. 6(b) displays the fitness iteration of the adaptive GA. The improved GA converged to the optimal solution in less than 40 iterations, while the adaptive GA had 100 iterations. This shows that the improved GA has more advantages than the adaptive GA in searching the optimal solution. When optimizing the communication anti-interference technology, the improved GA brings better performance. The fitness iteration of different initialization methods is shown in Fig. 7.

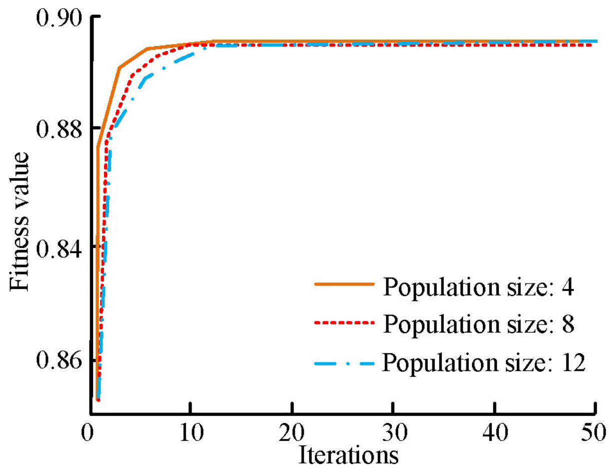


(a)

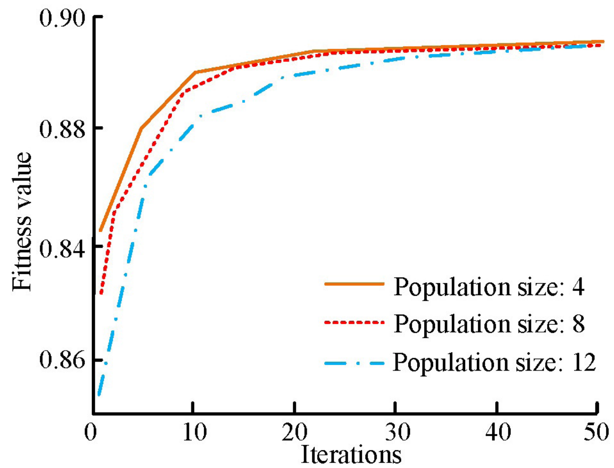


(b)

Fig. 5 The effect of different parameters on the performance, (a) Control paramteres, (b) Weighting coefficient



(a)



(b)

Fig. 6 Fitness iteration of different algorithms, (a) Improved GA, (b) Adaptive GA

The population size in Fig. 7(a) is 5. The fitness value of random initialization tended to be stable after 30 iterations, and the fitness value of chaotic initialization was stable after 15 iterations. The population size of Fig. 7(b) is 15. The fitness value of random initialization tended to be stable after 20 iterations, and the fitness value of chaotic initialization was stable after 10 iterations. The fitness convergence speed of chaotic initialization exceeds random initialization. The decision results of different decision engines are displayed in Table 1.

In Table 1, under broadband blocking interference, the average running time of adaptive GA and improved GA was 0.312s and 0.057s respectively, and the probability of convergence to the optimal solution was 99.3% and 100% respectively. Under partial band blocking interference, the average

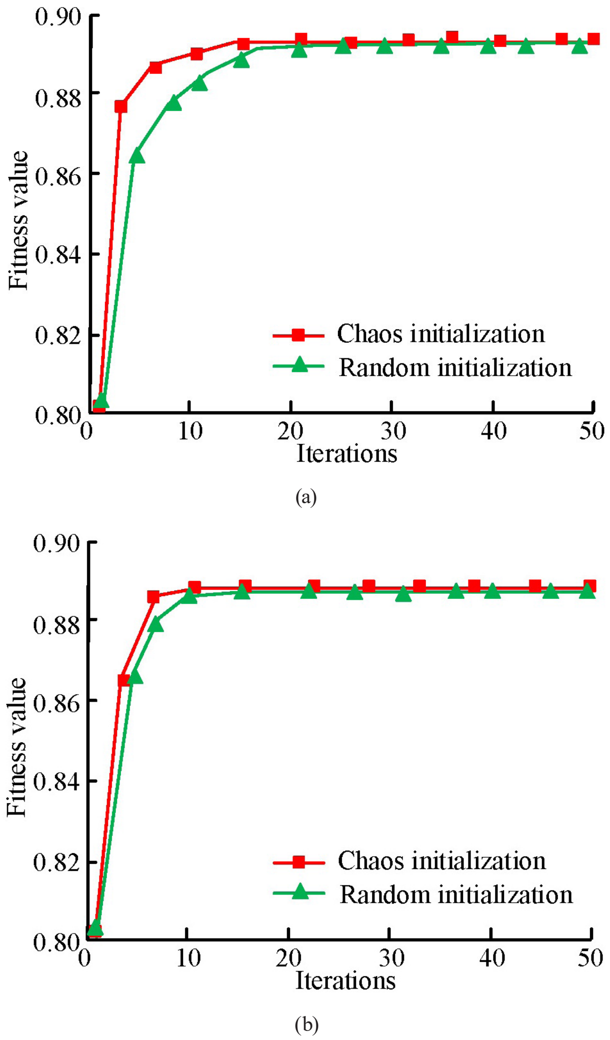


Fig. 7 Fitness iterations with different initialization methods, (a) Population size: 5, (b) Population size:14

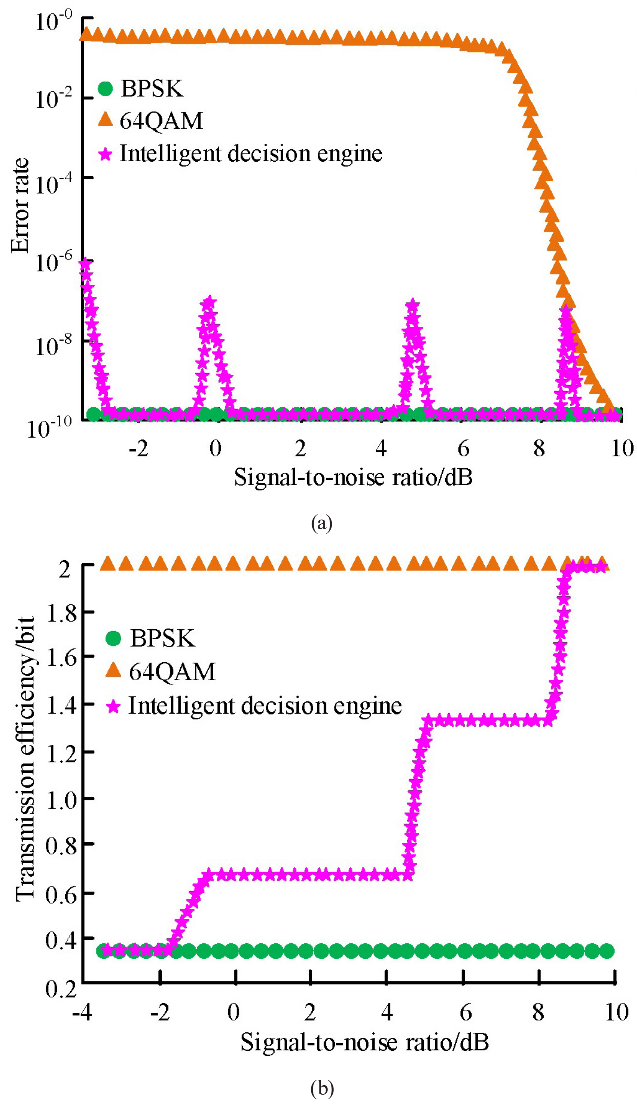


Fig. 8 Communication system performance of different methods, (a) Error rate, (b) Transmission efficiency

Table 1 Decision outcomes for various decision engines

Interference type	Algorithm	Average run time	Convergence probability
Broadband blocking	Adaptive GA	0.312s	99.3%
	Improved GA	0.057s	100%
Frequency band blocking	Adaptive GA	0.617s	86.3%
	Improved GA	0.134s	100%

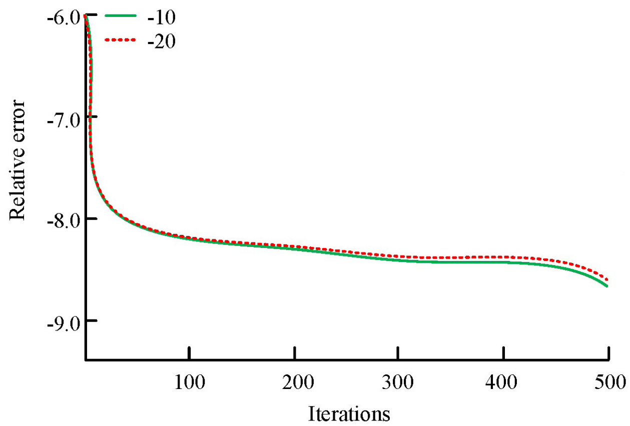
running time of adaptive GA and improved GA was 0.617s and 0.134s, respectively, and the probability of convergence to the optimal solution was 86.3% and 100%, respectively. The improved GA can solve the problem more effectively and improve the accuracy and efficiency of decision-making. To verify the effect of intelligent decision engine based on improved GA, Binary Phase Shift Keying (BPSK) modulation and 64 Quality Amplitude Modulation (64QAM) are used as comparison methods. The communication system performance of different methods is shown in Fig. 8.

Fig. 8(a) shows the bit error rate of the communication system after modulation by different methods. Fig. 8(b) shows the transmission efficiency comparison of communication systems after different methods. The frequency hopping communication system of intelligent decision engine had stronger anti-interference ability, which was suitable for the Signal-to-Noise Ratio (SNR) of −2db to 10dB. Compared with the conventional frequency hopping system with fixed BPSK modulation, its transmission efficiency was higher, and the bit error rate was less than 10^{-6}. In some cases of SNR, the error rate of the frequency hopping communication system of the intelligent decision engine will experience a jump, and the error rate will briefly increase, still below 10^{-6}. However, in this case, the transmission efficiency of the system will be significantly improved by 1.8–2.5 times. Frequency hopping communication systems have a certain degree of adaptability, able to tolerate changes in bit error rates to a certain extent and adjust transmission efficiency. This phenomenon also reflects the flexibility and adaptability of intelligent decision engines, making them highly reliable and stable in complex and changing environments. At the same time, this also provides a new idea for the practical application of communication systems, which is to improve the transmission efficiency and resource utilization of the system by optimizing communication strategies and algorithms while ensuring communication quality.

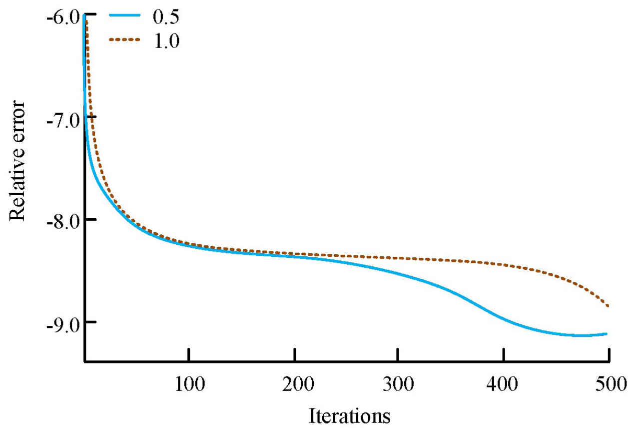
3.2 Application analysis of anti-interference frequency hopping sequence method

To verify the influence of control parameters χ_1 and χ_2 on the performance of the improved GWO, the control parameter χ_1 is set to −10 and −20 respectively, and the control parameter χ_2 is set to 0.5 and 1.0 respectively. The maximum number of iterations for the algorithm is 500, the population size is 40, and the algorithm runs independently 30 times. The convergence speed of the algorithm under different control parameters is shown in Fig. 9.

The control parameter χ_1 in Fig. 9(a) is set to −10 and −20 respectively. The control parameter χ_1 had no obvious effects on the convergence speed. The control parameter χ_2 in Fig. 9(b) is set to 0.5 and 1.0 respectively. When the value was 0.5, the convergence speed was faster. To ensure the performance of the improved GWO, the following experiments set the control parameters χ_1 and χ_2 to −10 and 0.5 respectively. To verify the improved GWO, the experiment compares the traditional GWO with the hybrid GWO. The test results of different algorithms under unimodal and multimodal functions are shown in Fig. 10.

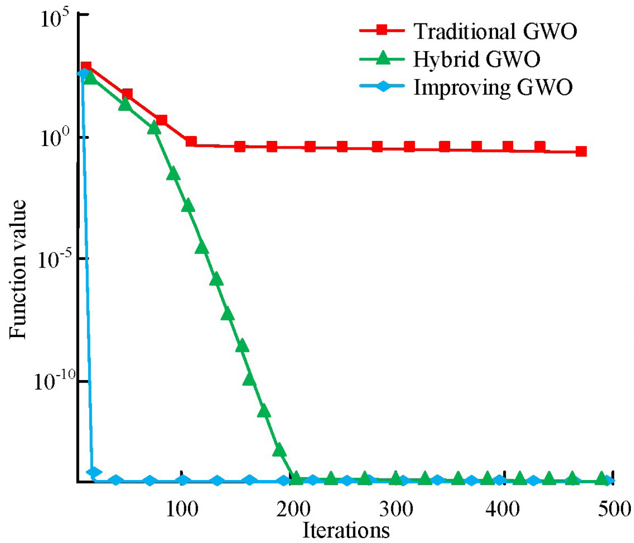


(a)

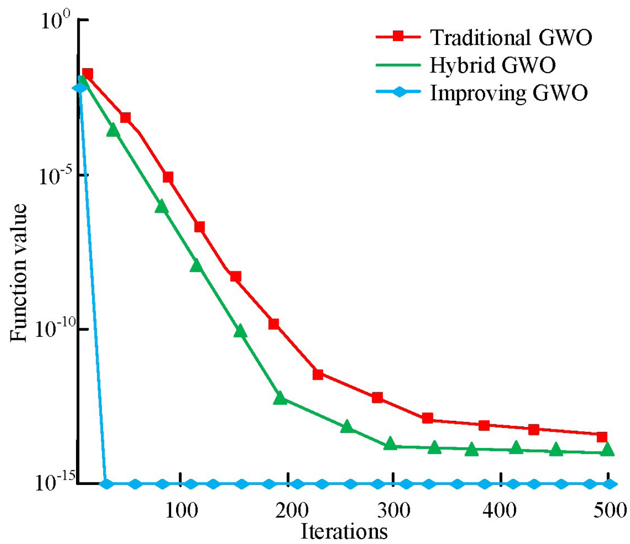


(b)

Fig. 9 Convergence rate of the algorithm under different control parameters, (a) χ_1, (b) χ_2



(a)



(b)

Fig. 10 Test results of different algorithms under unimodal and multimodal functions, (a) Test 1, (b) Test 2

Fig. 10(a) displays the results under the unimodal function. Fig. 10(b) displays the results under multimodal function. Compared with the traditional GWO and the hybrid GWO, the improved GWO had the fastest convergence speed, reaching the convergence state in the first 20 iterations. The improved strategies, such as the individual information exchange mechanism, the foraging trajectory of Levi flight simulation insects and the reverse learning strategy, make it jump out of the local optimum, so as to improve the convergence speed and stability. The performance curves of different algorithms are shown in Fig. 11. Total benefit refers to the cumulative reward obtained by the algorithm in the adversarial environment. Specifically, this benefit is the sum of immediate rewards obtained by the algorithm at each decision step based on the current state and actions taken. The total revenue is composed of the following parts added together. One is the reward obtained when the algorithm correctly identifies and successfully hops to an undisturbed channel. The second is the reward obtained by the algorithm for successfully avoiding interference when combating it. Thirdly, the algorithm reduces the rewards obtained from communication interruptions during the decision-making process by adopting effective strategies. These individual income values are dynamically calculated based on the performance of the algorithm during the simulation process and accumulated at each decision step, ultimately forming the total revenue curve shown in the Fig. 11. By comparing the total revenue curves of different algorithms, the performance of the algorithms in anti-interference decision-making problems can be evaluated.

Fig. 11(a) shows interference environment 1. Fig. 11(b) shows the performance curves of different algorithms in interference environment 1. The total revenue of the anti-interference frequency hopping sequence generated by the improved GWO algorithm reached 2310, which was about 9.5% higher than that of the traditional GWO and hybrid GWO. Fig. 11(c) shows interference environment 2. Fig. 11(d) shows the performance curves of different algorithms in interference environment 2. The total revenue of the anti-interference frequency hopping sequence generated by the improved GWO algorithm was 320, which was about 52.4% higher than that of the traditional GWO and hybrid GWO.

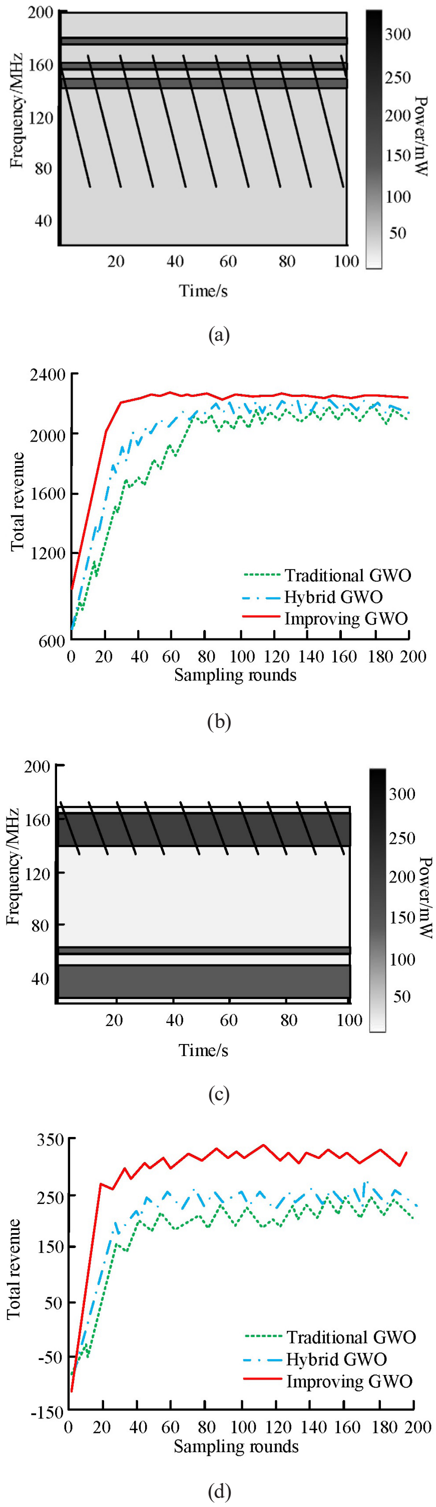


Fig. 11 Performance curves for different algorithms, (a) Interference environment 1, (b) Interference environment 1 test, (c) Interference environment 2, (d) Interference environment 2 test

4 Discussion and conclusion

The communication system is faced with complex environment and interference, including signal interference, frequency drift and so on. To improve the anti-interference of communication system, intelligent anti-interference technology based on improved GA and GWO algorithm was proposed. The improved GA used control parameters based on nonlinear changes to optimize the search process of

GA. Then an intelligent decision engine was built. GWO algorithm used individual information exchange mechanism and Levy flight to simulate the foraging trajectory of insects to optimize the search process. The experimental results showed that the frequency hopping communication system of intelligent decision engine had stronger anti-interference ability, which was suitable for the SNR of −2db to 10dB. Compared with the conventional frequency hopping system with fixed BPSK modulation, its transmission efficiency was higher, and the bit error rate was less than 10^{-6}. The total revenue of the improved GWO in anti-interference frequency hopping sequence was 2310, which was about 9.5% higher than that of traditional GWO and hybrid GWO. The intelligent anti-interference technology proposed in this paper makes the frequency hopping communication system have better anti-interference performance, providing guarantee for its application in complex environment. However, the limitation of the research is that it is limited to theoretical analysis and simulation experiments, which has not carried out the actual communication system test. Future research can refer to the modified Newton method to further optimize the relevant parameters and mechanisms of improving GA and GWO algorithms in intelligent anti-interference technology, in order to enhance their performance in practical applications. At the same time, practical communication system design and testing should be carried out to apply theoretical research results to practice, comprehensively verify the effectiveness and reliability of improved GA and GWO algorithms in real communication environments, and provide stronger support for the stable operation of communication systems in complex environments. At the same time, it is also possible to explore the integration with other optimization algorithms, as well as customized anti-interference strategies for different application scenarios, in order to bring more innovation and breakthroughs to the field of communication.

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