Multi-source, Multi-object and Multi-domain (M-SOD) Electromagnetic Interference System Optimised by Intelligent Optimisation Approaches

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Abstract With the wide use of electromagnetic information equipment, a large number of wireless radiation systems coexisting in the same region produce intentional or unintentional interference on electronic receivers. For the purpose of intentional electromagnetic interference, it is necessary to realise the efficient suppression of other receivers at little cost. When multiple transmitting sources are used to interfere with multiple receivers, the parameters of multiple transmitting sources are required to be comprehensively optimised and set so as to achieve a desired high-efficiency interference. The current parameter setting methods mainly focus on the selection of the parameters for a single receiver which is fulfilled by a single transmitter, or simple parameter selection among multiple receivers, which is fulfilled multiple transmitters, lacking optimisation methods aiming at parameter setting among multiple transmitting sources of multiple object receivers in multiple electromagnetic domain transmitters, *i.e.*, multi-source, multi-object and multi-domain (M-SOD) interference systems. Therefore, we propose a novel method with which to optimise the setting of parameters of an M-SOD interference system based on intelligent optimisation approaches. Furthermore, this study also builds an intelligent optimisation model, which contains multiple transmitters and receivers which involved many parameters include position, direction of space domain, frequency, bandwidth, and power. Then the model is abstracted to the problem of single-objective optimisation with constraints and optimised through a traditional GA and an improved FWA method. The extensive experiments and comparisons show that the solutions obtained by using intelli-

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gent optimisation approaches are superior to those of the conventional design method~~, so,~~ the proposed algorithm is an effective approach for setting the parameters of an M-SOD electromagnetic interference system.

Keywords Electromagnetic interference · Transmitting sources · Parameter setting · Intelligent optimisation · Evolutionary computation algorithm

1 Introduction

In the modern information society, people often depend on electromagnetic waves to acquire and utilise information, however, in this process, because various electromagnetic devices in the same region influence each other, it often happens that equipment fails to work normally [1]. Intentional and unintentional interference generally appears under the circumstance of military or civil tasks, such as electronic countermeasures on the battlefield, crosstalk in a telecommunication network, and radio interference. Owing to the problem of multi-device interaction becoming increasingly serious and inevitable, it is necessary for whether the interfering party or the interfered party to study interference problem [2]. The interfering party requires reasonable interference strategies to achieve interference effects and reduce the cost. While the interfered party needs to study the interference strategies adopted by the other party and propose corresponding defensive measures and anti-interference means, so as to improve the survival rate of equipment and reduce associated losses.

At present, although there is much literature on interference and anti-interference, the problems of multiple transmitting sources to multiple objective receivers in multiple electromagnetic domains parameter setting have not yet been reported. For the interfering party, it is very important to set parameters for interference transmitting equipment and parameters need to be set specifically according to electronic reconnaissance results. Owing to their wide scope of coverage, broadband omni-directional equipment does not need to set a particular frequency and antenna direction, while their operating distance is limited. To interfere with the remoter objective receivers, narrow frequency bands and directional antennas can be properly set on the premise of obtaining the reconnaissance parameters. When multiple transmitters are utilised to interfere with multiple receivers simultaneously, the method of parameter setting represents the selection of interference strategies to some extent, which significantly influences the results. For example, receivers with a similar frequency in the same region can be interfered with by a transmitter. On the contrary, the reasonable parameter setting can obtain satisfactory interference effects at low cost, such as is associated with a low transmission power. It is of great practical significance to reduce the transmission power of interference equipment to protect it from anti-interference equipment and anti-radiation weapons belonging to a hostile party.

To use intelligent optimisation approach to optimise the parameters of multiple transmitting sources for transmitting high-effective interference signal, first of all, it is necessary to establish a model for multiple transmitting sources to multiple objective receivers in multiple electromagnetic domains. The model proposed in the research includes multiple transmitters and receivers and parameters in multiple domains, such as position, direction, frequency, bandwidth, and power, all of which need to be optimised, so it is described as an M-SOD interference system model. The model can be extended. When the parameters, such as position, direction, frequency, and bandwidth are known, the corresponding relationship between interference transmitters and receivers can be determined. At this time, it is convenient to include the choices of the optimal interference pattern and encoding mode which have no influence on the existing parameters. In solving the model, this study utilises two intelligent optimisation approaches and compares them with a traditional experience-based algorithm, which verifies the effectiveness of the intelligent optimisation approaches.

The remainder of this paper is organised as follows: Section 2 introduces the related research work, in Section 3, the novel M-SOD interference system model is described, followed by the derivation of the formula governing the bit error rate (BER) of objective receivers based on the specific assumptions, Section 4 describes the solutions obtained by use of an intelligent optimisation approach, while the experiments are elaborated in Section 5, and then the conclusions.

2 Related work

2.1 Communication interference and anti-interference

At present, many research achievements have been made in the fields of communication interference and anti-interference. Most research into anti-interference aims at unintentional interference and such research generally analyses interference effects and then puts forward methods by which to reduce such adverse influences [3–7]. On the contrary, studies of communication interference (intentional interference) are divided into two categories: one-to-one communication interference and many-to-many communication interference according to the number of interfering and interfered parties.

The existing research on one-to-one communication interference focus on analysing interference effects of a single transmitter on a single receiver [8] and studying interference patterns. Other workers [9] have carried out theoretical analysis and simulation on performances of direct sequence spread spectrum system under monophonic interference. Elsewhere researchers [10] analysed the performances of an orthogonal frequency division multiplexing (OFDM) system under several different narrowband interference spectra. It was assumed that interference channels are additive white Gaussian noise channels or time-invariant Rayleigh fading channels. The selection of the best interference pattern attracts a wide spread attention. In general, the theories of parameter optimisation, such as game theory, particle swarm optimisation, and genetic algorithms (GA) can be used to seek optimal interference strategies to set power and signal patterns [11–13].

Many-to-many communication interference can be divided into two types according to different objects. One is distributed interference to communication network. In view of different characteristics of nodes and links in communication network, the interference strategies are designed separately to achieve interference on the whole communication network [14–16]. In some reports, game theory is used for analysing and modelling the relationship between the interfering, and interfered, parties [17–24] and the relevant equilibrium theories are adopted. The other is the optimal setting of parameters of many-to-many communication interference. In such research, problems are generally modelled according to the specific background and the optimisation of several parameters is studied, showing strong pertinence [25–28]. Of them, some [29,30] have investigated the deployment positions of equipment. For the deployment of interference position in a communication network without prior information, some teams [31] deduced the upper and lower bounds of the results of the problem through the steps for optimising the maximum number of grid points. Moreover, theoretical analysis proves that the method is superior to the traditional suppression method. By employing decision support systems, some workers [32,33] solved the optimisation strategies provided in the program package for assessing deployment positions under countermeasures of firepower systems, radar and communications systems, *etc.*; however, the specific schemes for determining candidate locations were not given. Literature [34] established the model for the deployment of transmitters in ground-to-air interference of unmanned aerial vehicle (UAV) groups and determined the optimal position by utilising a triangulation method and GA. Simulation experiment demonstrates that these two algorithms are superior to random deployment patterns. In addition, in view of different types of communication protocols, some literatures studied the interference in physical layer [35, 36] and link layer and obtained certain effects. In view of the specific communication protocol, literature [37] put forward the corresponding distributed interference strategies in link layer, so that good interference effects can be obtained by using a low transmission power.

Others generally only optimise a certain parameter: owing to many parameters being involved in practical problems, multi-parameter optimisation needs to be studied. In the field of intentional electromagnetic interference, due to numerous and various objective communication receivers, multiple interference equipment items are required for effective interference thereto. To achieve ideal interference effects, it is necessary to simultaneously set interference parameters in multi-domain: time, space, frequency, power, and code domains.

Differing from the existing literature, this study summarises the interference problem as the optimisation of M-SOD interference system parameters and deduces the signal expression and formula for communication BER for multiple transmitters to multiple receivers. Furthermore, the optimisation goal is set to achieve the interference effects with the minimum power. Owing to lots of parameters being involved, and the problem complexity, the intelligent optimisation approach is used for solving the problem.

2.2 Intelligent optimisation approach

Evolutionary computation, as the main part of the intelligent optimisation approach, is inspired by the genetic phenomenon of biological reproduction and natural selection mechanism of "survival of the fittest" in Darwinian theory. The algorithm imitates the phenomenon of survival, evolution and finally high adaptation of biological populations in the environment. By regarding the problem as environment, the evolutionary algorithm maintains a swarm with feasible solutions. By constantly generating new solutions and eliminating the poor solutions, the swarm is updated, so that the swarm finally finds the optimal solution to the problem. Evolutionary computation is mainly used for solving problems that are difficult to be solved by gradient-based method, such as discrete problem, multimodal problem, non-differentiable problem and even optimisation problems without analytic expression of the objective function. In the meantime, evolutionary computation algorithm can be quickly applied into the complex problems, like multi-objective optimisation and dynamic optimisation and shows advantages, such as good parallelizability. Therefore, it forms a big part of the current artificial intelligence boom.

Many scholars researched evolutionary algorithm and then proposed various computing methods successively. The typical representatives include Genetic Algorithm (GA), evolutionary strategy (ES), differential evolution (DE). Among them, GA is the basic and most widely used evolutionary algorithm. The algorithm was first proposed by Fraser [38,39] and then again by Bremermann [40] and Reed [41] *et al.*, and finally it has become widely used after much work by Holland. As another important algorithm, ES was put forward by Rechenberg [42,43] for the first time in 1960s and then further developed by Schwefel [44]. The core idea is the evolution of evolution, that is, the evolutionary method of living things itself is constantly updated in evolution. As for the algorithm, strategic parameters are continuously adjusted and evolved in the algorithm process. Storn and Price [45,46] proposed the DE in 1995. By utilising the unique differential variation method, the distance and direction information of the swarm are effectively utilised to guide the search.

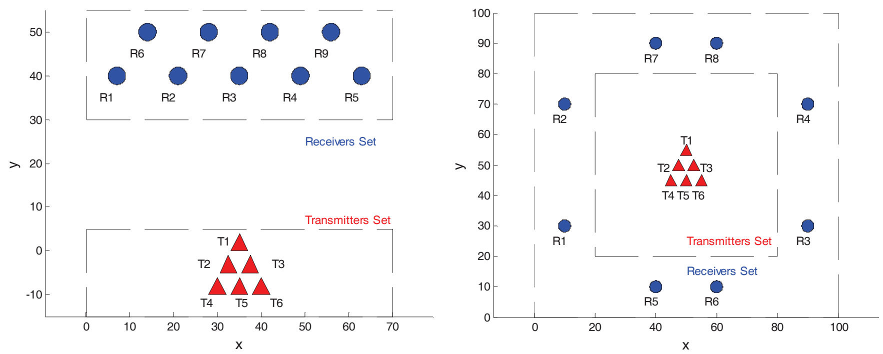
Furthermore, the evolutionary algorithm based on swarm intelligence is also a research hotspot and plays an important role in optimisation studies. The algorithms comprise the ant colony optimisation algorithm [47], particle swarm optimisation algorithm [48], bee colony algorithm [49], fish swarm algorithm [50], firefly algorithm [51], fireworks algorithm (FWA) [52], *etc.* Of them, the FWA [53] is a new swarm intelligence algorithm. It is a mathematical model for the behaviour of fireworks exploding in the air, and forms a parallel search method by introducing random factors and selection strategies. As a new swarm intelligence algorithm, the FWA has shown strong problem-solving ability since its inception. By using a new search mechanism, the algorithm can display both global and local search capabilities by adjusting the explosion radius of each firework in a swarm.

3 Proposed M-SOD interference system model

3.1 Scene description

The model proposed in the study contains multiple transmitters and receivers. The parameters to be set include position, direction, frequency, bandwidth, and power. Moreover, the space domain, time domain, frequency domain, and energy domain are designed, so the model is called the M-SOD interference system model. The scene settings of the model are shown in Figure 1. N radio receivers are distributed in the region without any influence on each other and there are M interference transmitters in the region which affect receivers in receiving signals. All receivers adopt omni-directional antennae, while directional antennae are used in all transmitters.

Owing to the position parameters of transmitters generally needing to be preset, without loss of generality, first this study designs the transmitter set into a triangular formation and presents its accurate position. For receivers, two layout scenes are designed as cases for test, as displayed in Figure 1.



(a) Centralised layout (b) Distributed layout

Fig. 1 Sketch scene map for the model (by taking the interference of six transmitters to eight or nine receivers as examples, the red and blue blocks represent the interference transmitters and communication receivers, respectively).

(1) Case 1: Centralised layout. The nine receivers are centralised in a specified closed area, locating in one side of the closed area of transmitters. The given parameter settings are listed in the following table.

(2) Case 2: Distributed layout. Eight receivers are dispersed around the periphery of the transmitters and the parameters of the receiver set are as set in the following table.

Table 1 Parameters of receiver and transmitter sets in Scene1

Receiver number	X position (km)	Y position (km)	Frequency (MHz)	Bandwidth (MHz)	Transmitter number	X position (km)	Y position (km)	Beam width (°)
1	7	40	2017.1	1.6	1	35	0	30
2	21	40	2018.8	1.6	2	32.5	-5	30
3	35	40	2019.2	1.6	3	37.5	-5	30
4	49	40	2018.3	1.6	4	30	-10	30
5	63	40	2016.6	1.6	5	35	-10	30
6	14	50	2016.2	1.6	6	40	-10	30
7	28	50	2017.9	1.6				
8	42	50	2017.5	1.6				
9	56	50	2015.8	1.6				

Table 2 Parameters of receiver and transmitter sets in Scene2

Receiver number	X position (km)	Y position (km)	Frequency (MHz)	Bandwidth (MHz)	Transmitter number	X position (km)	Y position (km)	Beam width (°)
1	10	30	2015.8	1.6	50	55	30	
2	10	70	2016.3	1.6	2	47.5	50	30
3	90	30	2016.8	1.6	3	52.5	50	30
4	90	70	2017.3	1.6	4	45	45	30
5	40	10	2017.7	1.6	5	50	45	30
6	60	10	2018.2	1.6	6	55	45	30
7	40	90	2018.7	1.6				
8	60	90	2019.2	1.6				

3.2 Interference computation model

It is assumed that the nth receiver $(x_{r,n}, y_{r,n})$ in the communication system can receive signals from the $m\,(m = 1, 2, ..., M)$th interference transmitter besides predetermined communication signals. Moreover, except for communication signals, there are only interference and AWGN noise in the system. The model meets the following assumptions:

(1) Radio receivers and interference transmitters are distributed in the two-dimensional plane in a specific range, without considering the elevation factor.

(2) Interference transmitters are definitely able to obtain various parameters of receivers and interference parameters are set accordingly.

(3) Transmitters have upper and lower bounds to parameters, such as bandwidth and energy.

The interference signals with noise amplitude modulation of the mth transmitter $(x_{t,m}, y_{t,m})$ are described thus:

$$J_{m,t}\left(t\right) = \left(U_m + U_n\left(t\right)\right) e^{j\left(2\pi f_m t + \theta_m\right)} \tag{1}$$

Where, U_m, f_m, θ_m represent the carrier power, frequency and phase, respectively and θ_m obeys uniform distribution in $[0, 2\pi)$. $U_n\left(t\right)$ indicates the baseband noise and white Gaussian noise is obtained through a low-pass filter. By changing the bandwidth of this baseband noise, the bandwidth of all interference signals can be adjusted accordingly. Considering other factors, such as signal propagation in space and the gains of the antenna transmitters and receivers, the power of signals received by each receiver at (x, y) in the coordinate system from the mth transmitter can be expressed as:

$$P_{m,r} = \frac{P_m F\left(\mathit{\Delta}\beta_m\right) G_r \lambda^2 L_b}{\left(4\pi R_m\right)^2} \tag{2}$$

Where, G_r and λ represent the gain and operating wavelength of receiving antenna, respectively. R_m indicates the distance to the mth transmitter and $R_m = \sqrt{\left(x - x_{t,m}\right)^2 + \left(y - y_{t,m}\right)^2}$. L_b denotes the mismatch loss of bandwidth. $F\left(\mathit{\Delta}\beta_m\right)$ shows the pattern function of the gain of the $F\left(\mathit{\Delta}\beta_m, \mathit{\Omega}\right)$ antenna of the mth transmitter and the directional angle of the transmitter is β_m (defined as the angle of X-axis rotating counter-clockwise around the origin to (x, y)). The angle of the coordinate (x, y) with the principal axis of beams is $\mathit{\Delta}\beta_m = |\beta_m - \beta_{x,y}|$ and $\beta_{x,y} = \begin{cases} \arccos\left(\frac{x - x_{t,m}}{R_m}\right), & y \geq y_{t,m} \\ 2\pi - \arccos\left(\frac{x - x_{t,m}}{R_m}\right), & y < y_{t,m} \end{cases}$.

The amplitude of signals from the mth transmitter arriving at each receiver can be expressed as:

$$J_m(t) = \sqrt{\frac{F\left(\mathit{\Delta}\beta_m\right) G_r \lambda^2 L_b}{\left(4\pi R_m\right)^2}} \left(U_m + U_n(t)\right) e^{j\left(2\pi f_m t + \theta_m\right)} \tag{3}$$

The interference channel of interference source is modelled as a time-varying Rayleigh fading channel [54]:

$$h_m(t) = \alpha_m e^{j\left(2\pi f_{d,m} t \cos\phi_m + \varphi_m\right)} \tag{4}$$

Where, α_m represents the channel fading range and is an independent and identically distributed Gaussian random variable with mean value and variance being 0 and σ_α^2 separately. $f_{d,m}$ indicates the maximum Doppler frequency shift caused by the movement of interference sources [55]. ϕ_m is the angle of arrival of received signals and follows a uniform distribution on $[0, 2\pi]$. φ_m denotes the random phase obeying the uniform distribution.

The total signals received by the nth receiver can be expressed as:

$$r_n(t) = \sqrt{P_s} x(t) c(t) + \sum_{m=1}^{M} h_m(t) J_m(t) + n(t) \tag{5}$$

Where, P_s indicates the power of spread spectrum signals from predetermined communication transmitter. $x(t)$ denotes the spread spectrum signal, meeting $E\left[x^2(t)\right] = 1$. $c(t)$ represents the spread spectrum code sequence. $n(t)$ denotes additive white Gaussian noise and its one-sided power spectral density (PSD) is N_0.

Formulae (3) and (4) are substituted into Formula (5) to obtain:

$$r_n(t) = \sqrt{P_s}x(t)c(t) + \sum_{m=1}^{M} \alpha_m \sqrt{\frac{F(\Delta\beta_m) G_r \lambda^2 L_b}{(4\pi R_m)^2}} (U_m + U_n(t)) e^{j[2\pi(f_d+f_m)t+\theta_m]} + n(t) \tag{6}$$

Dispreading is performed on the total received signals, thus giving:

$$r'_n(t) = \sqrt{P_s}x(t) + \sum_{m=1}^{M} h_m(t) J_m c^*(t) + n(t) c^*(t) \tag{7}$$

Where, $(\cdot)^*$ demonstrates the conjugate operation.

The instantaneous signal to interference plus noise ratio (SINR) γ of the receiver is[1]:

$$\gamma = \frac{P_s T_b}{|\alpha|^2 N_I + N_0} = \frac{E_b}{|\alpha|^2 N_I + N_0} = \frac{1}{|\alpha|^2 N_I / N_0 + 1} \frac{E_b}{N_0} \tag{8}$$

Where, $E_b = P_s T_b$ and T_b indicate the bit energy and symbol period, respectively. N_I represents the power spectral density of $\sum\limits_{m=1}^{M} h_m(t) J_m c^*(t)$ at f_0 and is closely correlated with the transmitter parameters. Furthermore, the average BER $p_{b,n}$ of the nth receiver is calculated as[2]:

$$p_{b,n} = \frac{1}{\pi} \int_0^{\pi/2} \int_0^{E_b/N_0} \frac{E_b/N_0}{2\sigma^2 \gamma^2 N_I/N_0} \exp\left(\frac{-\gamma^2}{\sin^2\varphi}\right) \times \exp\left(-\frac{E_b/\gamma N_0 - 1}{2\sigma^2 N_I/N_0}\right) d\gamma d\varphi \tag{9}$$

When the BER of receivers exceeds a certain threshold, it can be considered that interference effects are achieved. According to the above derivations, it is found that BER of receivers is closely correlated with the transmitter parameters. To realise interference, the power needs to be increased under the condition that the frequency and antenna beam are directed to receivers, so as to reduce the instantaneous SINR γ and increase BER $p_{b,n}$. If an interference transmitter suppresses multiple receivers, both the bandwidth and power need to be increased, thus raising the overall cost. Therefore, in an M-SOD interference system, the goal of optimising the setting of multiple transmitters is to obtain better interference effects at low cost (*e.g.*, transmitter power).

[1] The derivation is provided in Appendix 1.
[2] The derivation is provided in Appendix 2.

4 Principle and application design of the intelligent optimisation approach

The computation model used when optimising the setting of transmitters is complex, especially for the combined interference of multiple transmitters on multiple receivers: when the BERs of each receiver are calculated by using the forward model (Section 3.2), it is difficult to calculate the optimal parameters of transmitters by finding an analytical solution. A feasible design method is to set the parameters manually based on experience or constantly adjust the parameters of transmitters by using the trail-and-error method and observing the BER results; however, these methods generally depend on experience, need manual debugging and intervention, which lack flexibility, so they are unable to be extended to large-scale deployment.

The evolutionary algorithm of intelligent optimisation can be used to solve such problems. It can automatically learn and design parameters. The evolutionary algorithm has the following advantages in dealing with the research problems:

(1) As a black box optimisation method, the evolutionary algorithm regards the computing model as an objective function relating to parameter optimisation, while ignoring specific function form.

(2) The evolutionary algorithm is a stochastic optimisation method. Candidate solutions are randomly generated in the parameter space by means of population. The next generation of individuals is selected and generated according to certain mechanisms, showing good global convergence.

(3) The evolutionary algorithm can design a reasonable evaluation function (fitness function) so that the generated optimal solutions can have good properties on the basis of ensuring a solution.

The parameter setting method is proposed in the study and experiment is carried out based on the evolutionary algorithm. Through a traditional GA and an improved FWA method, namely loser-out tournament based fireworks algorithm (LoT-FWA), the interference computation model of receiver set is optimised. Moreover, the optimisation results and interference effects of the method are compared with a baseline method based on experience.

4.1 GA

In a GA, a population of candidate solutions (individuals) is evolved toward better solutions. A fitness function is to evaluate the solution domain. For the general minimisation problem, the smaller the fitness, the better the solution is. In a basic GA, the individuals are encoded with 01 vectors of fixed size. The evolution starts from randomly generated individuals. Through iterative process, the fitness of each individual is evaluated. The population keeps higher fitness individuals, and modifies each individual's genome by recombination and being possibly randomly mutated. Three operators, i.e. crossover, mutation and selection are the core in the iteration of GA. The framework of the GA is outlined below as Algorithm 1.

Algorithm 1 Framework of the GA

```
Establishing initial population P_0 and evaluating fitness, t = 0
while the termination condition is not met, do
    Crossover on population P_t
    Mutation on population P_t
    Evaluating the generated fitness of offspring
    Selecting population P_t and their generated offspring to obtain a new population P_{t+1}
    t = t + 1
end while
```

4.2 FWA

The Firework Algorithm (FWA) is a novel swarm intelligence algorithm inspired by a shower of sparks filling the local space around the firework. The FWA consists of four parts: an explosive operator, mutation operator, mapping rule, and selection strategy. The role of the explosive operator is to generate new sparks around the fireworks, and the number of generated sparks and the explosive range are determined by the explosive operator. Furthermore, the sparks generated through the mutation operator follow a Gaussian distribution. Under the effects of the two operators, the newly generated sparks are mapped to the feasible range by utilising the mapping rule and new sparks are selected as the next generation of fireworks through use of the selection strategy.

The framework of the FWA is outlined in Algorithm 2.

Algorithm 2 Framework of the FWA

```
Randomly selecting positions for n fireworks
while the termination condition is not met, do
    n fireworks
    for all fireworks x_i, do
        calculating the number S_i of sparks generated by each firework
        calculating the range A_i of sparks generated by each firework
    end for
    randomly generating sparks
    for k = 1 → m̂ do
        (m̂ represents the number of sparks generated from Gaussian mutation of fireworks)
        randomly selecting a firework x_i and generating a spark
    end for
    Mapping sparks according to the mapping rule
    Selecting the best fireworks and other fireworks in accordance with the selection strategy
end while
```

To improve the synergistic efficiency of fireworks, Li *et al.* [56] proposed an improved method based on the independent selection mechanisms. To be specific, for each firework, the progressive speed of the current generation is calculated. If the current generation cannot exceed the fitness of the optimal fireworks at the current progressive speed, it is a loser and needs to be reinitialised. The benefits are: 1) parameters in collaborative framework of fireworks algorithm are avoided. 2) Whether, or not, it is worthwhile to continue searching the region can be determined before fireworks get too close.

4.3 Parameter setting

(1) Genetic representation of the solution domain

For each transmitter, parameters to be optimised include directional angle of antenna (beta_m), power (Pm), frequency (f_tm) and bandwidth (f_bm). The corresponding optimisation ranges are summarised in Table 3.

Table 3 Value ranges of parameters to be optimised

	Min	Max
beta_m (radian)	0	2π
Pm (W)	0	1000
f_tm (/MHz)	2010	2025
f_bm (/MHz)	1.6	7

The parameters to be optimised are concatenated to form a 24-dimensional vector, that is, the dimension of the optimisation problem. The evolutionary algorithm maintains a population to seek the optimal solutions and each individual indicates a feasible solution to the problem. Each parameter is normalised on the interval (0, 1).

(2) Design of fitness

The fitness function is used to evaluate the solution domain (corresponding to the individual). The design of fitness is crucial to the convergence of optimisation algorithm and is expected to reflect the desired properties. The following aspects are mainly considered in the design of a fitness function:

a) L_{pbn}: BERs of all receivers have to meet certain requirements, which is the primary goal for interference. In the simulation experiments, without loss generality, it is assumed that the interference goal is satisfied when the BER of a receiver is larger than 0.2. No distinction is made as long as the BER is greater than 0.2, while more punishment should be given if it is less than 0.2. Therefore, a great punishment of linear attenuation is applied to solutions that do not meet the interference and the specific design is demonstrated as follows:

$$
\begin{aligned}
L_{pbn}^{i} &= \begin{cases} \dfrac{e^{10}-e^{1}}{0-0.2} pbn_i + e^{10} & , \ pbn_i < 0.2 \\ 0 & , \ pbn_i \geq 0.2 \end{cases} \\
L_{pbn} &= \sum_i L_{pbn}^{i}
\end{aligned} \tag{10}
$$

Where, i represents the ith receiver.

b) L_{Pm}: the sum of powers of all transmitters should be as small as possible.

$$
L_{Pm} = \sum_i Pm_i \tag{11}
$$

c) L_{Pm_dist}: the difference of powers should not be too large. If there is a transmitter with an extremely small transmission power, it has little or no influences on interference effects. This reduces fault tolerance on a transmitter set and robustness of interference effects and wastes setting resources.

$$
L_{Pm\_dist} = \max_i \{Pm_i\} - \min_j \{Pm_j\} \tag{12}
$$

d) L_{pbn_dist}: the difference of BERs of transmitters should be small. The consideration of this item is similar with L_{Pm_dist}, hoping to reach a uniform interference effect.

$$
L_{pbn\_dist} = \max_i \{pbn_i\} - \min_j \{pbn_j\} \tag{13}
$$

The overall fitness function is:

$$
\text{Fitness} = \lambda_1 L_{pbn} + \lambda_2 L_{Pm} + \lambda_3 L_{Pm\_dist} + \lambda_4 L_{pbn\_dist} \tag{14}
$$

Where, the hyper-parameters λ_i $(i = 1, 2, 3, 4)$ are used to indicate the importance of each term.

5 Experiments

5.1 Hyper-parameter setting

In the experiment, it is assumed that interference effect is reached when BER of each receiver is greater than 0.2. The parameters settings are $\lambda_1 = 1.0$, $\lambda_2 = 1.0$, $\lambda_3 = 10.0$, $\lambda_4 = 10.0$. For the GA, the elite selection mechanism is used. It ensures that the optimal individual or several optimal individuals are reserved to the next generation, while the other individuals adopt tournament selection mode. The number of populations is set to 2,000 and the number of elite individuals retained is 200. Moreover, the mutation probability is set to 0.1. For the Lot-FWA, the number of fireworks is 10 and the number of sparks is 500, while the other parameters are set with reference to the literature [56].

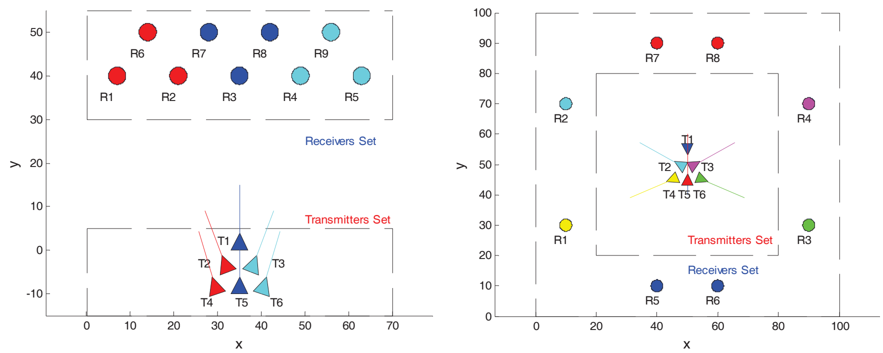
The generational process is repeated until a termination condition has been reached (when there is no obvious progress after 30 consecutive rounds.). Ten groups of experiments are repeatedly conducted in each case and the obtained best results are regarded as the optimal solution of the algorithm.

5.2 Baseline algorithm—traditional parameter setting method based on experience

In view of the two cases, the traditional parameter setting method based on experience is designed and the sketch map of interference in groups is shown in Figure 2 (the transmitters interfere with receivers of the same colour).

Case 1: considering the position and beam coverage, to give full play to the transmitters, the transmitters and receivers are separately divided into three groups, shown in three colours. The transmitters interfere with receivers of the same colour, for example, T1 and T5 interfere with receivers R3, R7, and R8. According to the situation of receivers, the parameters of corresponding transmitters are set. For instance, the centre frequencies of T1 and T5 are set at the points trisecting bandwidth covered by R3, R7, and R8. The directions are geometric centres of R3, R7, and R8.

Case 2: due to non-uniform distribution of receivers, R5 and R6 are divided into a group according to the coverage of beams and interfered with by T1. T5 interferes with the group consisting of R7 and R8. Moreover, the other four transmitters interfere with the four receivers, separately. When one transmitter interferes with two receivers, the parameters are set as follows: the centre frequency and beam direction of T1 are set to be the midpoint of the frequency band and geometric centre, respectively. In the situation of one transmitter interfering with one receiver, the corresponding transmitter is set according to the parameters of the receiver.



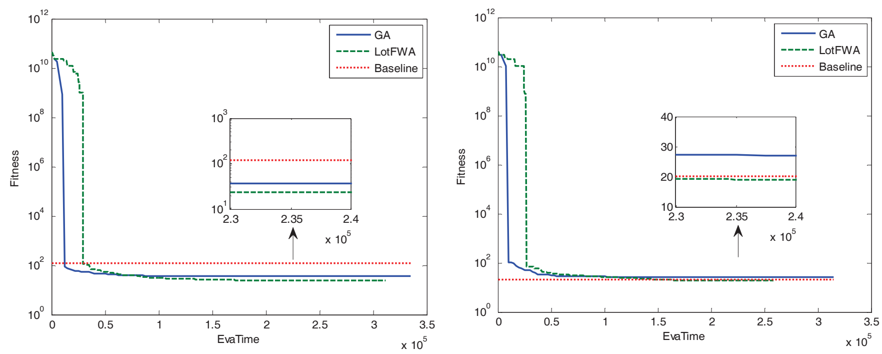
(a) Case 1 (b) Case 2

Fig. 2 Schematic diagram of empirical parameter setting method for interference in groups (transmitter sets of the same colour are designated to interfere with the same colour of receiver sets)

The power is uniformly set on a step-by-step basis, that is, the powers of transmitters (groups) are increased in certain step length (set to be 1 W in the experiment), until the corresponding receivers (groups) are completely interfered. Such a setting method based on experience completely neglects the interactions between transmitters (groups) and receivers (groups) not being interfered with by the former, which may waste a lot of resources. In addition, such a method requires prior knowledge of problem cases and needs geometric design and manual intervention, so it is difficult to be extended and applied in more complex cases.

5.3 Experimental result and its comparison analysis

5.3.1 Comparison of convergence of optimisation algorithms



(a) Case 1 (b) Case 2

Fig. 3 Comparisons of convergence in the optimisation of GA and LoT-FWA

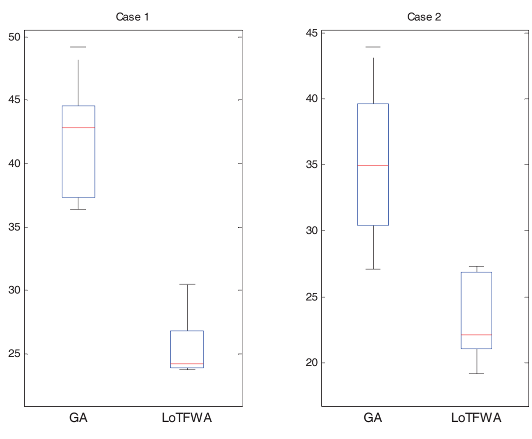
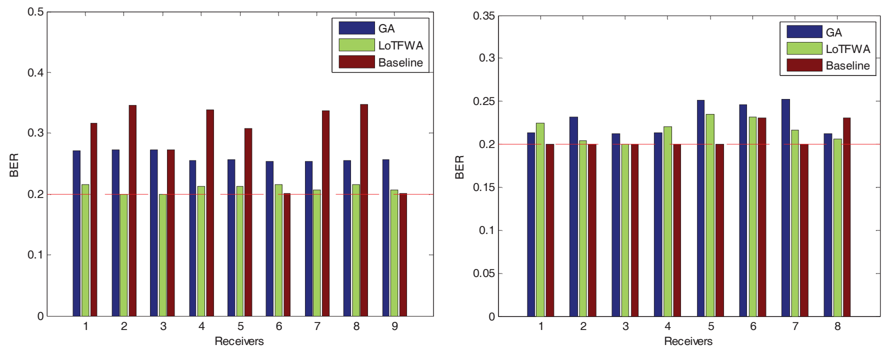


Fig. 4 Boxplots of fitness errors (the horizontal axis shows different scenes and algorithms, while the vertical axis indicates the average optimal fitness and error bar of the algorithms in each experiment)

Figure 3 shows the comparison of convergence of two optimisation algorithms: the horizontal axis represents the times of evaluating solutions using the algorithm and the vertical axis indicates the optimal fitness. Moreover, the dotted line shows the fitness corresponding to parameter setting as calculated by the baseline algorithm based on interference between groups. Figure 4 shows the boxplots of fitness at the end of optimisation. The horizontal axis shows different scenes and algorithms, while the vertical axis indicates the average optimal fitness and error bar of the algorithms in each experiment. It can be seen that these two algorithms finally converge within the acceptable range of fitness, indicating that the algorithms can achieve interference effects on all receivers and search the solution space better than the baseline algorithm. Based on the optimisation process of these algorithms, the response time of the GA is obviously better than that of the LoT-FWA, which is correlated with the encoding form of the individuals. As mentioned in Section 4.3, the parameters of each transmitter are combined to a long vector, while the GA shows an explicit crossover operation. This is favourable for information exchange in populations, thus searching the feasible solutions more quickly: however, prematurity arises quickly in a GA, so the final optimisation results of the GA are not as good as those arising from the use of LoT-FWA. LoT-FWA shows strong local search ability and maintains higher diversity, thus effectively avoiding the occurrence of prematurity. Furthermore, the algorithm is able to search the optimal solution constantly and the result after multiple operations is better, and more stable, than that of a GA. The key is that such loser-out mechanism of LoT-FWA can increase the probability of finding the globally optimal solution of the algorithm.

5.3.2 Interference effect

(1) BER



(a) BER in Case 1 (b) BER in Case 2

Fig. 5 Comparison of BERs of receivers (the horizontal axis represents the number of receivers, while the vertical axis indicates the corresponding BER values of receivers)

Figure 5 shows the comparison of interference effects on receiver groups. The horizontal axis represents the number of receivers, while the vertical axis indicates the corresponding BER values of receivers. It can be seen that the optimisation results of GA and LoT-FWA optimisation algorithms can interfere to all receivers in two cases. Moreover, the BER values of receivers are approximate, which meets the considerations required when designing a fitness function. The BERs of algorithms, when setting parameters based on experience (Baseline) in Case 1, are generally high. The reason for this is that, in the process of interference among groups, owing to the receivers being distributed on one side of the transmitters, a transmitter can interfere with receivers in other groups, so the while-loop used in such cyclic power adjustment wastes a lot of energy. The BER of optimisation results of the GA is generally higher than that of the LoT-FWA. This is because the GA first searches feasible solutions in the parameter space with a large power, while its local searchability is not better than the LoT-FWA, resulting in larger BER.

Table 4 Power comparison of transmitters

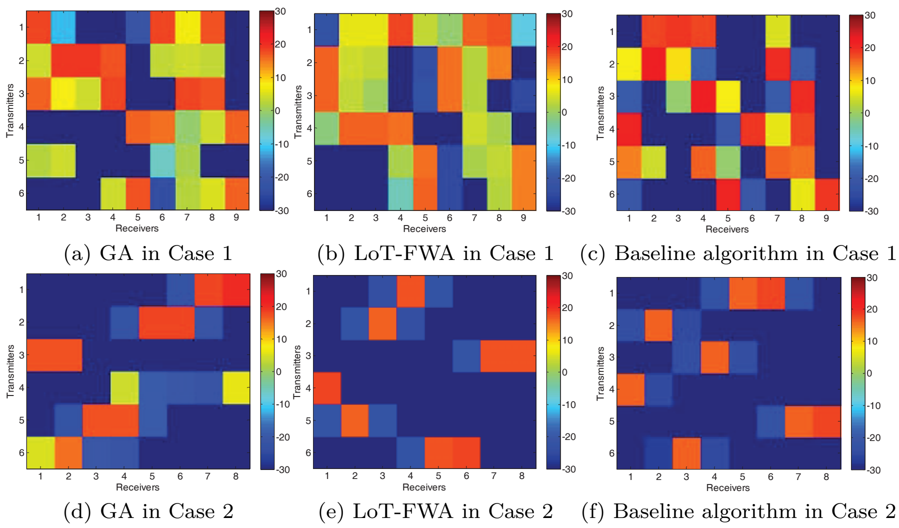
	Method	Sum of Pm (W)	Extreme deviation of Pm (W)
Case1	Baseline	4149	660
	GA	3606.29	0.99
	LoT-FWA	**2359.17**	**0.01**
Case2	Baseline	**1324**	65
	GA	2664.33	0.39
	LoT-FWA	1878.16	**0.01**

Table 4 lists the comparisons of powers of transmitters in optimisation results in different cases. The total transmission power and extreme deviation of transmission powers are compared: through the comparison, the total power of the optimal solutions obtained by using the GA is larger, while the results obtained by utilising LoT-FWA show more energy-saving effects. Although the total power of the baseline based on experience in Case 2 is lower, the method has a higher extreme deviation of power and needs to be used by virtue of geometric design and manual intervention, so it is difficult to be extended and applied in complex cases.

(2) Interference to signal ratio (ISR)

The ISR is defined as the logarithm of ratio of power of interference signals entering the receivers to that of the communication signals. It reflects the interference effects of each transmitter on each receiver. The experience shows that when ISR $\in$ [10, 15]dB, the corresponding transmitters induce strong interference on the receivers.

Figure 6 shows the ISR map: each receiver is affected by strong interference from at least one transmitter. Especially in Case 1, transmitters have strong interference effects on multiple receivers. If a transmitter cannot work due to some fault, interference can also be maintained to its maximum extent, which reflects the redundancy and robustness of swarm intelligence. In Case 2, owing



(a) GA in Case 1 (b) LoT-FWA in Case 1 (c) Baseline algorithm in Case 1

(d) GA in Case 2 (e) LoT-FWA in Case 2 (f) Baseline algorithm in Case 2

Fig. 6 map of interference to signal ratio (the horizontal axis represents the number of receivers, while the vertical axis indicates the number of transmitters. Moreover, the value in matrix shows the interference effect of the corresponding transmitters on receivers, namely, the value of interference to signal ratio (ISR))

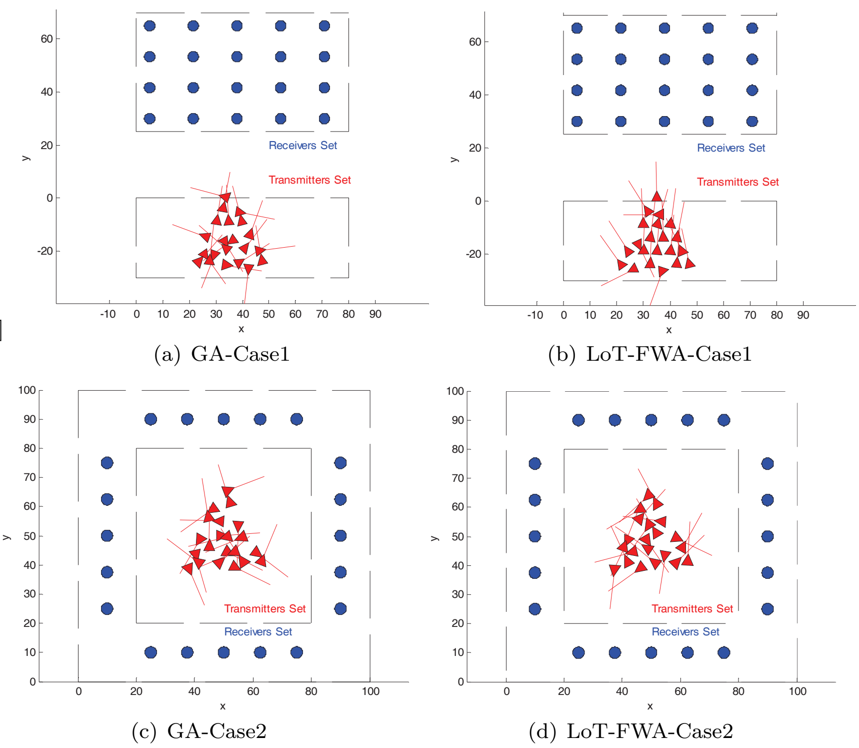
to the disperse distribution of receivers around transmitters and limitation of directional angle of antenna, it is very difficult for a single transmitter to impart strong interference to multiple receivers simultaneously while exerting a less intense interference effect.

5.3.3 Large-scale interference tasks

To verify the effect of intelligent optimisation approaches in large-scale radiation interference scenarios, we conducted extensive verification experiments in both scenarios (central layout and distributed layout). Adjusting the number of transmitters and receivers to 21:20, we still use the two evolutionary algorithms (GA and LoT-FWA) in the text for parameter optimisation. The parameter to be optimised is 84 dimensions, which becomes a high-dimensional optimisation problem.

Figure 7 shows the schematic diagram of the interference task. Figure 8 shows the convergence comparison of the algorithm. Figure 9 shows the ISR mapping of the transmitter to the receiver.

[!h]



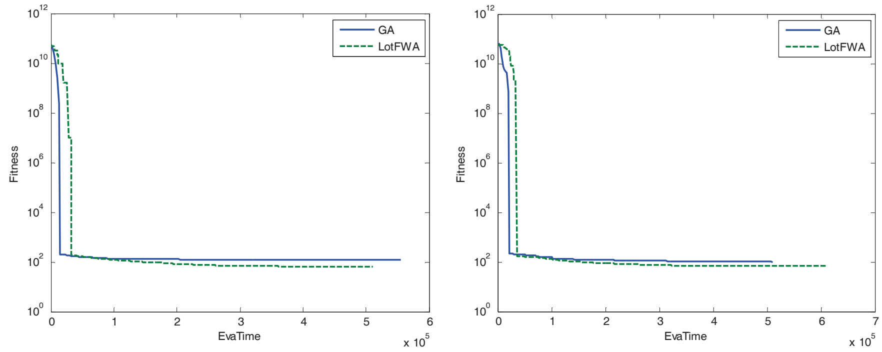
(a) GA-Case1 (b) LoT-FWA-Case1

(c) GA-Case2 (d) LoT-FWA-Case2

Fig. 7 Sketch maps of 21:20 (# of Transmitters: # of Receivers)

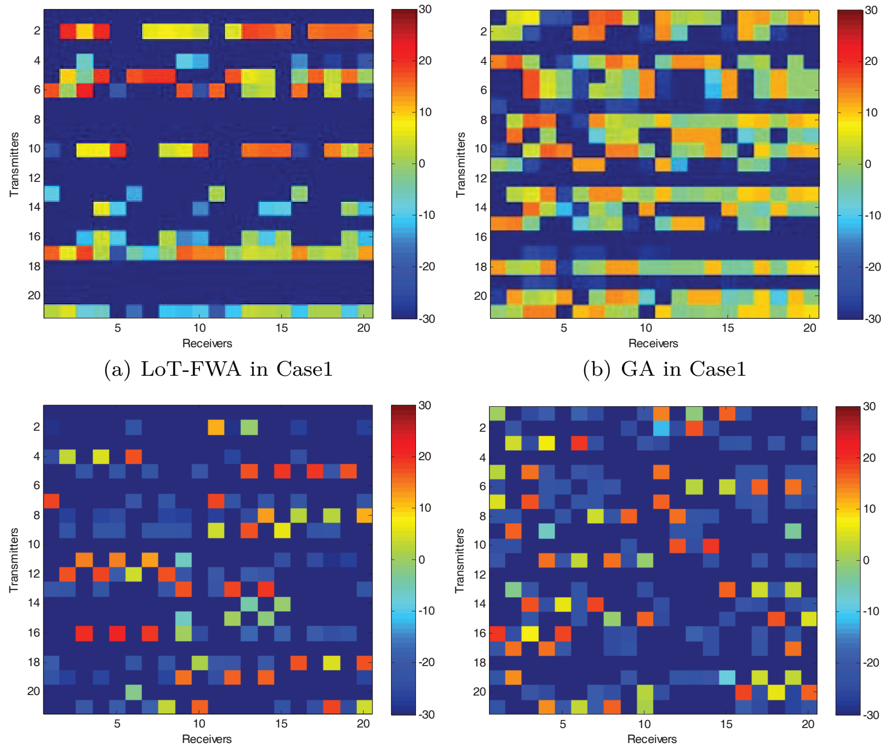
Table 5 The number of invalid transmitters

The number of invalid transmitters	Case 1	Case 2
GA	14	7
LoT-FWA	3	3



(a) GA-Case1 (b) LoT-FWA-Case1

Fig. 8 Converge Curve



(a) LoT-FWA in Case1 (b) GA in Case1

(c) LoT-FWA in Case2 (d) GA in Case2

Fig. 9 Map of ISR

In the scenario of large-scale interference task, the experience-based manual parameter setting method will be very complicated and cumbersome, and the evolutionary algorithm can adjust the automatic learning parameters based on the feedback composed of the fitness value. It can be seen, from Figure 8, that the response time of LoT-FWA is not as good as that of GA algorithm, but it converges to a better solution, which is consistent with our conclusion in Section 5.3.1. From the interference effect of the generator set to the interfering party in Figure 9, when the scale of the problem is raised, the solution obtained by the optimisation algorithm has some redundancy (that is, some transmitters do not impart any effective interference to any receiver). The combined effect of transmitters makes it possible for us to complete all tasks without needing more transmitters: however, from another point of view, maintaining a certain redundancy is beneficial to the robustness of the system. Table 5 lists the number of invalid transmitters in the optimisation results. It is not difficult to see that the LoT-FWA algorithm is more redundant, that is, each transmitter can interfere with multiple receivers as much as possible. This characteristic will be beneficial to the whole interference system when confronted with unexpected conditions (for example, if there are sudden failures in some transmitters).

6 Conclusions

Even though the studies of electromagnetic interference of electronic equipment attract much attention, there is still no study, available in practice, on the problems inherent to parameter setting of multi-source, multi-object and multi-domain (M-SOD) interference systems. In view of the setting problem of interference parameters in a complex electromagnetic environment, we established an M-SOD interference system model, which contains multiple transmitters and receivers which involved many parameters include position, direction of space domain, frequency, bandwidth, and power. In optimisation calculations, the model is abstracted to the problem of a single-objective optimisation with constraints. Owing to many parameters being involved, better effects cannot be obtained by using the traditional method, so this study solved the problem by utilising the intelligent optimisation approach.

To verify the effectiveness of the model and algorithm, a comparison experiment with the baseline algorithm is carried out, which demonstrates the efficacy of the intelligent optimisation approach to solving such interference problems. Moreover, parameter setting that meets the interference effects can be found in the feasible region of parameters of transmitters and there is no need for an explicit optimisation function expression. The comparison experiment indicates that the proposed intelligent optimisation approach is superior to the method designed based on experience, and that it obtains optimal solutions and also reduces energy consumption, therefore making it an effective method for optimising the setting of parameters for transmitters.

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Appendices

Appendix 1: derivation of instantaneous SINR γ

In the research, the communication mode used in the interfered communication system is TD-SCDMA and the uplink data frame structure is shown in Figure 10 [57]. The structure comprises two data blocks in the length of 352 chips, a midamble code (training sequence) in the length of 144 chips and a guard interval in the length of 16 chips.

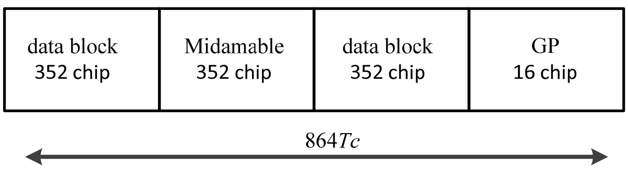


Fig. 10 Data frame structure of TD-SCDMA system (GP represents the guard interval and T_c indicates the chip period)

Assuming that the spread spectrum code sequence $c(t)$ is a PN code, the autocorrelation function of this PN code can be expressed as:

$$R_c(t) = \begin{cases} 1 - |\tau|/T_c & |\tau| \leq T_c \\ 0 & |\tau| > T_c \end{cases} \tag{15}$$

Where, T_c represents the chip period. The power spectral density function of PN code is obtained via the Fourier transform of the autocorrelation function:

$$S_c(t) = \mathbf{F}(R_c(t)) = T_c Sa^2(fT_c) \tag{16}$$

Where, $\mathbf{F}$ indicates the Fourier transform, and

$$Sa(x) = \frac{\sin(\pi x)}{\pi x} \tag{17}$$

Supposing that the interference signals are independent, the correlation function and the power spectral density of $J_{m,t}(t)$ are given by:

$$R_J(\tau) = \left(U_m^2 + R_{U_n}(\tau)\right) e^{j2\pi f_m \tau} \tag{18}$$

$$\begin{aligned} S_J(f) &= U_m^2 \delta(f - f_m) + S_{U_n}(f - f_m) \\ &= \frac{F(\varDelta\beta_m) G_r \lambda^2 L_b}{(4\pi R_m)^2} \left(U_m^2 \delta(f - f_m) + S_{U_n}(f - f_m)\right) \end{aligned} \tag{19}$$

The power of $J_{m,t}(t)$ is $P_m (P_m = U_m^2 + R_{U_n}(0))$, where $R_{U_n}(\tau)$ indicates the autocorrelation function.

If it is assumed that the channels are classical Clarke spectra, the autocorrelation function of $h_i(t)$ is:

$$R_h(\tau) = J_0\left(2\pi f_{d,i}\tau\right) \tag{20}$$

Where, $J_0(t)$ denotes the first-class zero-order Bessel function. The power spectral density of $h(t)$ is:

$$S_h(f) = \begin{cases} \frac{1}{\pi f_{d,i}} \frac{1}{\sqrt{1-(f/f_{d,i})^2}} & |f| < f_{d,i} \\ 0 & \text{else} \end{cases} \tag{21}$$

Assuming that $h_i(t)$, $J_i(t)$, and $c(t)$ are independent, the autocorrelation function of $\sum\limits_{i=1}^{Q_n} h_i(t) J_i(t) c^*(t)$ is:

$$R(\tau) = \sum_{i=1}^{Q_n} R_h(\tau) R_J(\tau) R_c(\tau) \tag{22}$$

According to the property of convolution, the power spectral density function of $\sum\limits_{i=1}^{Q_n} h_i(t) J_i(t) c^*(t)$ is:

$$\begin{aligned} S(f) &= \sum_{m=1}^{M} S_h(f) * S_J(f) * S_c(f) \\ &= \sum_{m=1}^{M} \frac{1}{\pi f_{d,m}} S_h(f) * \frac{F(\varDelta\beta_m) G_r \lambda^2 L_b}{(4\pi R_m)^2} \left(U_m^2 \delta(f - f_m) + S_{U_n}(f - f_m)\right) * T_c Sa^2(fT_c) \\ &= \sum_{m=1}^{M} \frac{T_c}{\pi f_{d,m}} \frac{F(\varDelta\beta_m) G_r \lambda^2 L_b}{(4\pi R_m)^2} \left\{U_m^2 S_h(f) * Sa^2[(f - f_m) T_c] + S_h(f) * S_{U_n}(f - f_m) * Sa^2(fT_c)\right\} \\ &= \sum_{m=1}^{M} \frac{T_c}{\pi f_{d,m}} \frac{F(\varDelta\beta_m) G_r \lambda^2 L_b}{(4\pi R_m)^2} \left\{\frac{U_m^2}{\sqrt{1 - (f/f_{d,m})^2}} * Sa^2[(f - f_m) T_c] + S_h(f) * S_{U_n}(f - f_m) * Sa^2(fT_c)\right\} \\ &= \sum_{m=1}^{M} \frac{T_c}{\pi f_{d,m}} \frac{F(\varDelta\beta_m) G_r \lambda^2 L_b}{(4\pi R_m)^2} \left\{\int_{-f_{d,m}}^{f_{d,m}} \frac{U_m^2 Sa^2[(f - t - f_m) T_c]}{\sqrt{1 - (t/f_{d,m})^2}} dt + S_h(f) * S_{U_n}(f - f_m) * Sa^2(fT_c)\right\} \end{aligned} \tag{23}$$

Supposing that f_0 is the carrier frequency, the power spectral density of $\sum\limits_{m=1}^{M} h_m(t) J_m c^*(t)$ at f_0 is:

$$N_I = S(f_0) \tag{24}$$

Supposing that the power spectral density function of received noise $n(t)$ is $S_n(f)$, the power spectral density of $n(t)\, c^*(t)$ at f_0 is:

$$S_{nc}(f_0) = S_n(f_0) * S_c(f_0) = \int_{-\infty}^{\infty} N_0 S_c(f - f_0)\, df = N_0 \tag{25}$$

The received instantaneous SINR γ is:

$$\gamma = \frac{P_s T_b}{|\alpha|^2 N_I + N_0} = \frac{E_b}{|\alpha|^2 N_I + N_0} = \frac{1}{|\alpha|^2 N_I/N_0 + 1} \frac{E_b}{N_0} \tag{26}$$

Where, $E_b = P_s T_b$ denotes the bit energy and T_b represents the symbol period.

Appendix 2: derivation of BER

Based on the literature [58], the average BER of the nth receiver is:

$$p_{b,n} = \int_0^{\infty} Q\left(\sqrt{2\gamma}\right) p(\gamma)\, d\gamma \tag{27}$$

Where, $Q(x) = \frac{1}{2\pi} \int_x^{\infty} \exp\left(-\frac{u^2}{2}\right) du$ and $p(\gamma)$ indicates the probability density function of γ. According to the probability density function of $|\alpha|$[58]:

$$p(|\alpha|) = \frac{|\alpha|}{\sigma^2} \exp\left(-\frac{|\alpha|^2}{2\sigma^2}\right) \tag{28}$$

Thus:

$$p(\gamma) = \frac{E_b/N_0}{2\sigma^2 \gamma^2 N_I/N_0} \exp\left(-\frac{E_b/\gamma N_0 - 1}{2\sigma^2 N_I/N_0}\right) \tag{29}$$

$Q(x)$ can be expressed as [58]:

$$Q(x) = \frac{1}{\pi} \int_0^{\pi/2} \exp\left(\frac{-x^2}{2\sin^2\varphi}\right) d\varphi \tag{30}$$

In accordance with the literature [58], the average BER of QPSK modulation is:

$$p_{b,n} = \frac{1}{\pi} \int_0^{\pi/2} \int_0^{\infty} \exp\left(\frac{-\gamma^2}{\sin^2\varphi}\right) p(\gamma)\, d\gamma d\varphi \tag{31}$$

Substituting Formula (29) into Formula (31) gives:

$$p_{b,n} = \frac{1}{\pi} \int_0^{\pi/2} \int_0^{E_b/N_0} \frac{E_b/N_0}{2\sigma^2 \gamma^2 N_I/N_0} \exp\left(\frac{-\gamma^2}{\sin^2\varphi}\right) \times \exp\left(-\frac{E_b/\gamma N_0 - 1}{2\sigma^2 N_I/N_0}\right) d\gamma d\varphi \tag{32}$$

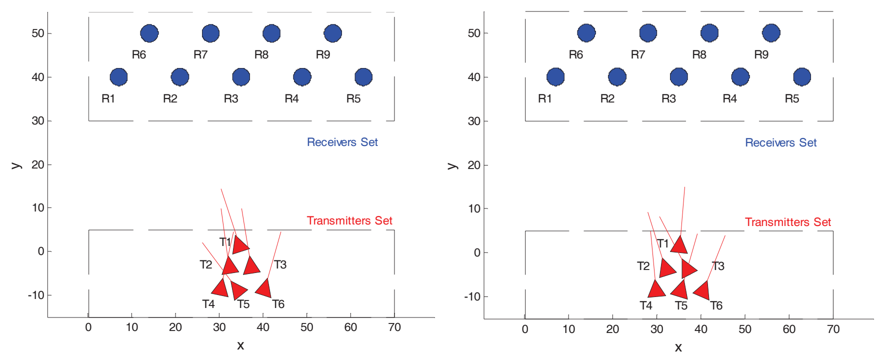
Appendix 3: parameter design table

1. Solutions in Case 1
   (1) Parameter optimisation result

Table 6 Parameter optimisation results of different algorithms in Case 1

Solution	Transmitter number	Power (W)	Directional angle of antenna (rad)	Frequency (MHz)	Bandwidth (MHz)
Baseline	1	430.0	1.5708	2018.9	1.10
	2	1090.0	1.9364	2018.19	1.3833
	3	1090.0	1.2052	2017.77	1.3833
	4	1090.0	1.8623	2016.81	1.3833
	5	430.0	1.5708	2017.8	1.10
	6	1090.0	1.2793	2016.38	1.3833
GA	1	600.77	1.8842	2016.81	2.3411
	2	600.95	1.7116	2018.98	6.9738
	3	600.81	1.7313	2017.86	1.6082
	4	601.76	1.3494	2016.12	2.5589
	5	600.79	2.2063	2020.05	6.4888
	6	601.21	1.2988	2016.24	4.1537
LoT-FWA	1	393.2	1.4807	2017.82	2.53
	2	393.19	1.8828	2016.79	6.7815
	3	393.19	2.0511	2016.39	5.4053
	4	393.2	1.6651	2019.0	2.9856
	5	393.2	1.29	2016.19	4.1654
	6	393.19	1.1953	2016.17	2.9592

(2) Sketch maps



(a) GA (b) LoT-FWA

Fig. 11 Parameter optimisation result of evolutionary algorithm in Case 1 (the red and blue rectangles represent the interference transmitter and communication receiver and the short line indicates the antenna direction).

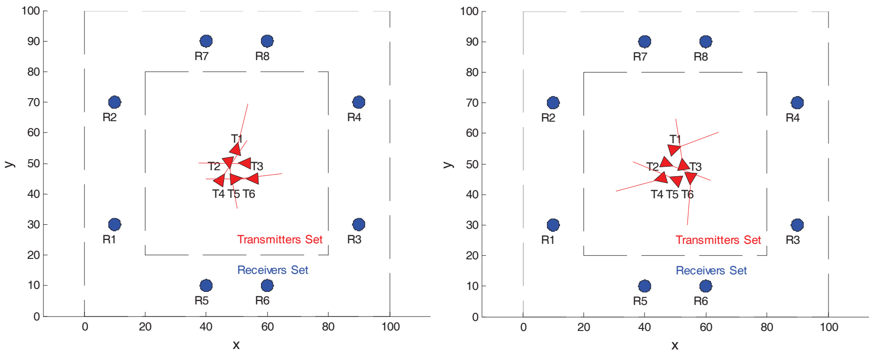
2. Solutions in Case 2

(1) Parameter optimisation result

Table 7 Parameter optimisation results of different algorithms in Case 2

Solution	Transmitter number	Power (W)	Directional angle of antenna (rad)	Frequency (MHz)	Bandwidth (MHz)
Baseline	1	249.0	4.7124	2017.99	0.2429
	2	229.0	2.6516	2016.29	1.6
	3	229.0	0.4910	2017.26	1.6
	4	184.0	3.5465	2015.8	1.6
	5	249.0	1.5708	2018.96	0.2429
	6	184.0	5.8783	2016.77	1.6
GA	1	444.2	1.3262	2018.61	6.9679
	2	444.16	4.8907	2017.92	5.0927
	3	443.81	3.1378	2015.97	1.7873
	4	444.15	0.9905	2018.21	1.9301
	5	444.2	0.1145	2017.08	1.6017
	6	443.81	3.1565	2016.94	1.8430
LoT-FWA	1	313.03	0.35867	2017.37	5.1312
	2	313.03	5.906	2016.78	4.2202
	3	313.02	1.7235	2018.95	2.7720
	4	313.03	3.4086	2015.48	4.8264
	5	313.02	2.7533	2016.25	2.0198
	6	313.03	4.6349	2017.86	3.6067

(2) Sketch maps



(a) GA (b) LoT-FWA

Fig. 12 Parameter optimisation results of evolutionary algorithms in Case 2