Research Article
Intelligent Integration Method of AI English Teaching Resource Information under Multi-Agent Collaboration

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In order to improve the intelligent effect of English teaching in the era of intelligent education, this article conducts an intelligent integration system of AI English teaching resources and information on the basis of multi-agent collaboration. Moreover, this article analyzes the principles and properties of the three algorithms, ALO, GWO, and MFO, and integrates them into the D2D power allocation problem in the two communication modes. In addition, this article studies the effects of population size, variable dimension, and convergence on the overall energy efficiency and generation of D2D users through simulation and combines improved algorithms to construct an intelligent integration system of AI English teaching resources and information under multi-agent collaboration. The simulation experiment study shows that the intelligent integration system of AI English teaching resources and information under the multi-agent writing proposed in this article can play an important role in the integration of English teaching resources and information.

1. Introduction
For English teaching managers, a comprehensive understanding of the information related to English translation teaching can better guide the development of English translation teaching activities. At present, although English translation information resources are rich in content and variety, the lack of integration of English information resources makes it inconvenient for users to obtain [1]. The integration of English information resources is to organically combine different types and carriers of English information resources, their services, and systems. Moreover, it optimizes and reorganizes the huge information resources of a large number of existing heterogeneous systems according to the inherent knowledge relationship between resources to form a systematic and intelligent resource aggregate, thereby providing more convenient information services [2]. The advantage of the integrated English information resource service is that it provides users with powerful information resource retrieval and information acquisition capabilities. At present, the organization of English information resources mainly adopts navigation catalogs to classify and gather English information resources under relevant categories and then publish them on the Internet to realize the sharing of English information resources [3].

English website information resources realize the classification and aggregation of English information resources in the form of navigation catalogs, and English literature information resources are mainly stored in virtual databases related to English [4]. For example, the collections of English libraries and the digital information resources of English literature collected by universities or English research institutions have been partially shared, but the information resources of English websites and English literature have not been shared, and the information resources of websites established by government departments at all levels and universities and English science and education departments have not been shared. Although the number of English websites is relatively large, the information resources on
English websites are small in scale; the information on the websites is updated slowly; the information lacks timeliness, accuracy, and authority; and the information resource construction of the English department is fragmented and lacks a unified development and integration planning, each in its own way, the degree of integration and sharing of information resources is low [5]. There are many kinds of English information resources. In addition to the traditional physical resources and paper resources, in the Internet environment, there are more and more network information resources, and the forms of English information are diversified [6].

There are different opinions on the concept of information resource integration. Literature [7] defines information resource integration. The so-called information resource integration refers to the clustering of data content, functional structure, and retrieval methods in each relatively independent resource system according to retrieval requirements. Reorganization is to provide a unified retrieval platform and display of retrieval results for information users. Literature [8] believes that the so-called information resource integration refers to the complete integration of information from different sources and different communication protocols through intermediate technology (digital resource seamlessly link integration software system) according to certain needs and requirements, so that different types of information can be integrated. Digital resources in different formats can be seamlessly linked. Through the integrated digital resource system, with an integrated retrieval function, it is a new type of digital resource system that is cross-platform, cross-database, and cross-content [9].

The integration of information resources can be understood from two aspects: from the content level, it can be understood as the use of modern information technology to compress the text, images, sounds and images of traditional media according to actual needs and according to certain norms and standards. Convert it into digital information, and sort and process the information according to its importance from the perspective of user needs, so that the social value of the information is enhanced, thereby adding value-added potential [10]. A fusion of digital resources between heterogeneous digital libraries [11].

The application of information technology will bring many changes to the education and teaching work. Classroom teaching is the core work of school education and the main channel to promote students’ learning and development. How to integrate information technology and subject course teaching, and use “integration” research and practice to drive and promote the reform and development of education in the context of information technology has become the focus of people’s general attention [12]. The launch of the education informatization project has improved the education and scientific research network system, built a modern distance teaching system, enriched the public education information resource base, provided an environmental guarantee for learning and information technology, and promoted education reform. The establishment of information technology education courses has created conditions for the integration of information technology and subject course teaching, as well as the exploration of learning and teaching theory and practice in the context of information technology [13].

As information resources have been widely concerned and utilized by human society, the concept of information resource integration has emerged as the times require. “Integration” means that there are often multiple elements in a system, and these elements are either scattered or unconnected, but they penetrate and connect with each other to form a whole system [14], and through integration, seemingly disparate and unconnected elements can be linked together to maximize their effectiveness. As a result, some scholars define the integration of information resources from the characteristics of information resources: fixed within a certain spatial range, various types of information resources are formed into an organic whole by means of logic and physics to achieve the effect of improving management and services. Some scholars define it from its development trend: under the unified leadership of the organization, the sharing and coordination of information resources, and the efficient and convenient acquisition of information resources can be realized, so as to deeply excavate its value and become the embodiment of the comprehensive competitiveness of the organization. No matter which point of view, the integration of information resources is described from the perspective of “comprehensive” and “all-round,” emphasizing the use of modern technology and means to make overall planning and comprehensive management of information resources [15].

The information resources of modern economy and society are showing the trend of “explosive” growth. Whether it is the quantity, structure, distribution, type, connotation, dissemination method, etc. of information, they all break through the tradition and are constantly enriched and developed. All this has resulted in the complex, diverse, and cumbersome characteristics of information resource integration objects. If there is no effective management mechanism, it will result in the “fragmentation” of a large number of information resources and increase the retrieval burden [16]. Whether it is for the development of universities or society, it is difficult to play a role in promoting, but it will increase the burden of information resource processing. Therefore, there must be a set of effective means to centrally integrate these scattered information resources and link them in an orderly manner. Through the retrieval system, the resources can be easily obtained and utilized efficiently [17].

The integration of information resources is defined as collecting various information resources from different information sources, then putting them into the channel, cooperating with each other, infiltrating and effectively controlling each part of the system, and finally passing it to the information sink. The process of screening, classifying, comparing, judging, associating, and reasoning about the acquired information resources using logical or physical methods, and arranging and synthesizing effective information for the purpose of maximizing benefits [18]. With the continuous development of society and the continuous
advancement of science and technology, human beings have officially entered the era of knowledge economy, and the types and quantities of information resources have shown a state of rapid growth, and even information resources have exploded. Under such conditions, the redundancy and disorder of information, the phenomenon of information island is inevitable, and a large number of information resources cannot be used to create value. To solve this problem, it is necessary to integrate information resources [19].

The richness and variety of information resource integration are mainly manifested in the following two aspects: First, the information processing means are rich and diverse. The process of realizing the integration of information resources is based on cutting-edge information technology. Only when colleges and universities have a variety of means of collecting, screening, and processing resources can they truly realize the function of integrating information resources in colleges and universities. Second, the information output forms are rich and diverse. When the information resources collected by colleges and universities have undergone a series of processing, they will use a variety of output forms, such as pictures, videos, sounds, reports, etc., to convey to the information users, and the specific output form depends on specific issues detailed analysis [20].

This article builds an intelligent integration system of English teaching resources and information based on AI on the basis of multi-agent collaboration to improve the effect of intelligent information integration in English teaching.

2. D2D Resource Allocation Algorithm based on Swarm Intelligence Optimization

2.1. System Model and Problem Description. In a single-cell system, in order to maximize the overall energy efficiency of DUs in the system as the objective function, this article studies the problems of power control, relay selection, and mode selection in D2D communication assisted by slow-moving relays.

Therefore, the established objective function can be described as:

\[
\text{EE}(P_s, P_r, P_c) = (1 - \mu) \text{EE}^d + \mu x_{ij} \text{EE'}, \quad j \in \mathbb{R}, \ i \in \mathbb{N},
\]

\[
\max_{P_s, P_r, P_c} \sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{R}} \text{EE}(P_s, P_r, P_c),
\]

s.t. \( \mu_i \in [0, 1], \forall i \in \mathbb{N}; \ x_{ij} \in [0, 1], \forall i \in \mathbb{N}, \forall j \in \mathbb{R}, \)

\[
\sum_{j \in \mathbb{R}} x_{ij} \leq 1, \quad \forall i \in \mathbb{N}; \ \sum_{i \in \mathbb{N}} x_{ij} \leq 1, \forall j \in \mathbb{R},
\]

\[
0 \leq P_s \leq P_{\text{max}}, 0 \leq P_r \leq P_{\text{max}},
\]

\[
U^d(P_s, P_c) \geq U_{\text{min}}, U^r(P_s, P_c) \geq U_{\text{min}},
\]

\[
R_c = \text{BW} \log_2(1 + \text{SINR}_c) \geq R_{\text{min}},
\]

\[
R'r = \frac{\text{BW}}{2} \left[\log_2(1 + \text{SINR}'_c) + \log_2(1 + \text{SINR}''_c)\right] \geq R_{\text{min}},
\]

where \( \mu_i \) represents the mode selection factor, \( x_{ij} \) represents the relay selection factor, and formulas (6)–(8) ensure the minimum transmission rate requirements of the DU and CU in the system in the two communication modes.

2.2. Algorithm Analysis. Obviously, the power allocation problem should be solved in two communication modes: direct connection and relay. Then, the energy efficiency optimization problem in D2D direct connection mode can be simplified as follows:

\[
\max_{P_s} \sum_{N} \text{EE}^d(P_s) = \sum_{N} \text{BW} \log_2 \left(1 + \frac{P_s h_{sd} / \eta_{c, d} h_{c, d} + N_0}{1 + \eta_{c, d} h_{c, d} / \eta_{c, r} h_{r, d} (P_{\text{min}} h_{c, d} + N_0)}\right),
\]

s.t. \( P_{\text{min}} \leq P_s \leq P_{\text{max}}. \)

The energy efficiency optimization problem in D2D relay mode can be simplified as follows:

\[
\max_{P_s} \sum_{N} \text{EE}^r(P_s) = \sum_{N} \frac{\text{BW} / 2 \log_2 \left(1 + \frac{P_s h_{sd} / \eta_{c, r} h_{r, d} (P_{\text{min}} h_{c, d} + N_0)}{1 + \eta_{c, r} h_{r, d} (P_{\text{min}} h_{c, d} + N_0)}\right) P_s + 2 P_{\text{CIR}}}{1 + \eta_{c, r} h_{r, d} (P_{\text{min}} h_{c, d} + N_0)}
\]

s.t. \( P_{\text{min}} \leq P_s \leq P_{\text{max}}. \)
where $P_{c_{\text{min}}}^d$ and $P_{c_{\text{min}}}^r$ are the minimum transmission power of the CU in the direct connection and relay modes, respectively, $P_{\text{max}}^d$ and $P_{\text{min}}^d$ are the upper and lower boundaries of the transmission power of the D2D transmitter in the direct connection mode, and $P_{\text{max}}^r$ and $P_{\text{min}}^r$ are the upper and lower boundaries of the transmission power of the D2D transmitter in the relay mode.

Next, three algorithms, MFO, GWO, and ALO, are introduced to solve the power distribution problem in the two communication modes.

The MFO algorithm is a global optimization algorithm inspired by the lateral positioning and navigation of moths at night and the spiral flight around the fire. In MFO, the moth is a search agent, assigning the best position of the moth so far to the flame, and each moth will search and update the position around the corresponding flame, and then continue to move closer to the best position. In this chapter, the position of the moth is the transmission power of the D2D transmitter in the system, and the solution for the optimal flame position is the solution for the optimal transmission power. The specific optimization process is as follows:

(1) Initialize the population. In MFO, the variable of the optimization problem is the position of the moth, the moth population size is $n$, and the number of variables (dimension) is $d$. The location matrix formula of the moth population is expressed as follows:

$$ M = [M_{ij}]_{n \times d} \quad (13) $$

The location matrix of the moth population should be defined as the transmission power matrix of the DU, where $n$ is the number of search agents, $d$ is the number of D2D user pairs, and the formula is expressed as follows:

$$ M = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1d} \\ P_{21} & P_{22} & \cdots & P_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nd} \end{bmatrix} \quad (14) $$

The searchable space of variables should be the limited range of DU transmission power, and the formula is expressed as follows:

$$ lb_j \leq P_{ij} \leq ub_j (i = 1, 2, \ldots n, j = 1, 2, \ldots d), \quad (15) $$

where $ub_j$ and $lb_j$ are the upper and lower boundaries of the $j$th DU ($j \in \mathbb{N}$) transmission power, and its value is defined as

$$ lb_j = \begin{cases} P_{\text{min}}^d & \text{When in D2D direct connection mode}, \\ P_{\text{min}}^r & \text{When in D2D relay mode}, \end{cases} $$

$$ ub_j = \begin{cases} P_{\text{max}}^d & \text{When in D2D direct connection mode}, \\ P_{\text{max}}^r & \text{When in D2D relay mode}. \end{cases} \quad (16) $$

The upper bound matrix $ub$ and the lower bound matrix $lb$ store the upper and lower bounds of all DU, respectively.

$$ lb = [lb_1, lb_2, \ldots, lb_d], $$

$$ ub = [ub_1, ub_2, \ldots, ub_d]. \quad (17) $$

For all moths, we define an array $OM$ to store their fitness function values, as shown in the following formula:

$$ OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix}. \quad (18) $$

Similarly, if the position matrix that defines the flame and the moth population matrix are of the same dimension, the position matrix and fitness function value matrix of the flame are shown in the following formula:

$$ F = \begin{bmatrix} F_{11} & F_{12} & \cdots & F_{1d} \\ F_{21} & F_{22} & \cdots & F_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ F_{n1} & F_{n2} & \cdots & F_{nd} \end{bmatrix}, $$

$$ OF = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix}. \quad (19) $$

(2) Moth location update. Each moth will spiral around a specific flame, and its mathematical model formula is expressed as follows:

$$ \vec{D}_t = |F_j - M_{ij}|, \quad (20) $$

$$ M(t + 1) = M(t) \cdot e^{bl} \cdot \cos(2\pi l) + F_j, \quad (21) $$

where $\vec{D}_t$ is the distance vector from the $i$th moth to the $j$th flame, $b$ is a constant defining the shape of the logarithmic spiral, and $l$ represents a random number between $[-1, 1]$. This parameter determines the distance between the moth’s position and the flame at the next moment. $l = -1$ means the moth is at the position closest to the flame, and $l = 1$ means the moth is at the position farthest from the flame. In order to further enhance the development ability of moths, we set $l$ to be a random number between $[r, 1]$, $r$ is called the convergence constant, and $r$ will decrease linearly from $-1$ to $-2$.

At the same time, the number of flames will be adaptively reduced in the MFO algorithm, and its mathematical formula is expressed as follows:
Flame_num = round\left( {N_F - t \times \frac{N_F - 1}{T}} \right),

(22)

where \(N_F\) is the maximum number of flames, \(t\) is the current number of iterations, and \(T\) is the maximum number of iterations. That is, at the beginning of the iterative process, there are \(N_F\) flames, and until the end, the moths will only update their positions around one optimal flame. This flame adaptive mechanism helps balance the exploration and development capabilities of the MFO algorithm and also improves the optimization efficiency.

To sum up, in the D2D direct connection mode, the fitness function of the MFO is formula (9). In the D2D relay mode, the fitness function of the MFO is formula (11). The setting of the flame in the MFO algorithm can save the best position in each iteration, and this one-to-one mechanism can avoid local optima.

The GWO algorithm sets four levels of \(\alpha, \beta, \delta,\) and \(\omega\) according to the social level of gray wolves, of which the first three are the optimal, second-best, and third-best solutions, respectively. The \(\omega\) wolf will follow the position of the first three wolves to continuously approach the prey, so as to find the global optimal solution. In this chapter, the position of the wolf is the transmission power of the D2D transmitter in the system, and the process of finding the optimal \(\alpha\) wolf position is the process of finding the optimal transmission power of the D2D transmitter.

Gray wolf hunting mechanisms include stalking, encircling, and aggressive behavior. The mathematical model formula for the enclosing behavior is expressed as follows:

\[
\overrightarrow{D} = \left| \overrightarrow{C} \cdot \overrightarrow{X}_p (t) - \overrightarrow{X}_f \right| ,

\overrightarrow{X} (t + 1) = \overrightarrow{X}_p (t) - \overrightarrow{A} \cdot \overrightarrow{D},
\]

(23)

where \(\overrightarrow{A}\) and \(\overrightarrow{C}\) are coefficient vectors, \(\overrightarrow{D}\) is the distance vector of the gray wolf to the target prey, and \(\overrightarrow{X}_p\) and \(\overrightarrow{X}_f\) are the position vectors of the prey and the gray wolf, respectively. \(\overrightarrow{A}\) and \(\overrightarrow{C}\) are defined as follows:

\[
\overrightarrow{A} = 2 \overrightarrow{a} \cdot \overrightarrow{r}_1 - \overrightarrow{r}_1 ,

\overrightarrow{C} = 2 \cdot \overrightarrow{r}_2 ,
\]

(24)

(25)

where \(\overrightarrow{a}\) decreases linearly from 2 to 0, \(\overrightarrow{r}_1\) and \(\overrightarrow{r}_2\) are random vectors between [0, 1] in an iterative process. Then in this chapter, the position matrix \(\overrightarrow{X}\) should be defined as the power matrix of the DU, and the formula is expressed as

\[
\overrightarrow{X} = [P_{ij}]_{n \times d},
\]

(26)

where \(n\) is the number of individuals in the gray wolf population, that is, the number of search agents; \(d\) is the number of variables, that is, the number of D2D user pairs; and the value range of \(P_{ij}\) is shown in formula (15).

We assume that \(\alpha, \beta,\) and \(\delta\) wolves are closer to their prey, and \(\omega\) wolf gradually kills their prey according to their guidance. That is, other search agents will update their own positions based on the best, second-best, and third-best search agent positions. Its mathematical model formula is expressed as follows:

\[
\begin{align*}
\overrightarrow{D}_a &= \left| \overrightarrow{C}_1 \cdot \overrightarrow{X}_a (t) - \overrightarrow{X}_f \right| , \\
\overrightarrow{D}_\beta &= \left| \overrightarrow{C}_2 \cdot \overrightarrow{X}_\beta (t) - \overrightarrow{X}_f \right| , \\
\overrightarrow{D}_\delta &= \left| \overrightarrow{C}_3 \cdot \overrightarrow{X}_\delta (t) - \overrightarrow{X}_f \right| , \\
\overrightarrow{X}_1 &= \overrightarrow{X}_a (t) - \overrightarrow{A}_1 \cdot \overrightarrow{D}_a , \\
\overrightarrow{X}_2 &= \overrightarrow{X}_\beta (t) - \overrightarrow{A}_2 \cdot \overrightarrow{D}_\beta , \\
\overrightarrow{X}_3 &= \overrightarrow{X}_\delta (t) - \overrightarrow{A}_3 \cdot \overrightarrow{D}_\delta . \\
\overrightarrow{X} (t + 1) &= \frac{\overrightarrow{X}_1 + \overrightarrow{X}_2 + \overrightarrow{X}_3}{3}
\end{align*}
\]

(27)

where \(\overrightarrow{X}_1, \overrightarrow{X}_2,\) and \(\overrightarrow{X}_3\) respectively represent the corresponding moving position vectors when the \(\omega\) wolf only targets the \(\alpha, \beta,\) and \(\delta\) wolves as prey. \(\overrightarrow{A}_1, \overrightarrow{A}_2, \overrightarrow{A}_3, \overrightarrow{C}_1, \overrightarrow{C}_2,\) and \(\overrightarrow{C}_3\) will be calculated according to formulas (24) and (25).

To sum up, in the D2D direct connection mode, the fitness function of GWO is formula (9), and in the D2D relay mode, the fitness function of GWO is formula (11). The coefficient \(|\overrightarrow{A}|\) in the GWO algorithm can balance the ability of exploration and development. When \(|\overrightarrow{A}| < 1\), it is suitable for local development, and when \(|\overrightarrow{A}| > 1\), it is suitable for global exploration, and the coefficient \(|\overrightarrow{C}|\) reflects the difficulty of gray wolf approaching its prey.

The ALO algorithm imitates the process of antlions killing ants by introducing random walks, roulette, and elite strategies. In ALO, the antlion digs a trap in the sand and waits for the prey ant at the bottom of the trap. Once the ant falls into the trap, the antlion will prey on it and reconfigure the trap. In this chapter, the position of the antlion is the transmission power of the D2D transmitter in the system, and the process of finding the position of the elite antlion is the process of finding the optimal transmission power of the D2D transmitter. The specific process is divided into the following four stages:

1. Ant random walk stage. The algorithm establishes the random walk movement model of the prey ant, and its formula is expressed as follows:

\[
X (t) = \left[ 0, \text{cumsum} (2r(t_1) - 1), \text{cumsum} (2r(t_2) - 1), \ldots, \text{cumsum} (2r(t_3) - 1) \right],
\]

(28)
where cumsum is the cumulative sum of the calculation, \( T \) is the maximum number of iterations, and \( r(t) \) is a random function whose value is defined as follows:

\[
r(t) = \begin{cases} 
1, & \text{When } k > 0.5 \text{ Time,} \\
0, & \text{When } k \leq 0.5 \text{ Time,} 
\end{cases}
\]

where \( t \) is the current iteration number and \( k \) is a random number between [0, 1].

\( M_{\text{ant}} \) is the position matrix of the ant population, and its form is similar to that of the moth population in the MFO algorithm, as shown in formula (30).

\[
M_{\text{ant}} = [A_{ij}]_{n \times d'}
\]

where the size of the ant population is \( n \), the number of variables (dimension) is \( d \), and \( A_{ij} \) represents the value of the \( j \)th variable of the \( i \)th ant. The fitness value formula corresponding to the ant population is expressed as:

\[
M_{\text{OA}} = \begin{bmatrix}
f([A_{11}, A_{12}, \ldots, A_{1d}]) \\
\vdots \\
f([A_{1n}, A_{n2}, \ldots, A_{nd}])
\end{bmatrix}
\]

where \( f \) is the objective function.

At the same time, the antlion also establishes traps in the searchable space, and it has the same dimension as the ant population, then the position matrix and fitness value matrix of the antlion population are as follows:

\[
M_{\text{antlion}} = [A_{lij}]_{n \times d'}
\]

\[
M_{\text{OAL}} = \begin{bmatrix}
f([A_{l11}, A_{l12}, \ldots, A_{l1d}]) \\
\vdots \\
f([A_{lnn}, A_{ln2}, \ldots, A_{lnnd}])
\end{bmatrix}
\]

where the \( f \) is the fitness function, the larger the fitness value of the antlion, the larger the trap it digs, and the easier it is to capture ants.

In this chapter, the location matrix of the antlion population should be defined as the transmission power matrix of the DU, where \( n \) is the number of search agents, \( d \) is the number of D2D user pairs, and the formula is expressed as follows:

\[
M_{\text{antlion}} = [P_{ij}]_{n \times d}
\]

where the value range of \( P_{ij} \) is shown in formula (15).

In order to limit the random walk of ants in the searchable range, formula (21) is normalized by formula (34).

\[
X_i^t = \frac{(X_i^t - a_i)(d_i^t - c_i^t)}{(b_i - a_i)} + c_i^t,
\]

where \( b_i^t \) and \( a_i \) are the maximum and minimum values of the random walk of the \( i \)th variable, respectively, and \( d_i^t \) and \( c_i^t \) are the maximum and minimum values of the \( i \)th variable in the \( t \)th iteration, respectively.

(2) The ants enter the trap stage, and the random walk of the ants in the trap will be affected by the antlion. The mathematical model formula is expressed as follows:

\[
c_i^t = \text{antlion}_j^t + c^t
\]

\[
d_i^t = \text{antlion}_j^t + d^t,
\]

where \( d^t \) and \( c^t \) is the maximum and minimum values of all variables in the \( t \)th iteration, respectively, and antlion\(_j\) is the position of the \( j \)th antlion at the \( t \)th iteration. The lion with the best fitness in each iteration is set as the elite lion, and the existence of the elite lion will affect the random walk of ants. At the same time, roulette and elite strategy are used to update the position of ants in a balanced manner, which can avoid falling into local optimum, and its formula is expressed as

\[
\text{ant}_j^t = \frac{R_A^t + R_E^t}{2}
\]

where \( R_A^t \) and \( R_E^t \) are the random walk of ants around the roulette strategy and the elite antlion at the \( t \)th iteration, respectively.

(3) When the ants are trapped in the trap, the antlions will prevent the ants from escaping the trap by throwing sand outwards, so the ants will keep sliding to the bottom of the trap until they are eaten by the ant lions. This sliding process of ants can be understood as the gradual reduction of the trap boundary. It is modeled as:

\[
c^t = \frac{c^t}{I},
\]

\[
d^t = \frac{d^t}{I},
\]

where \( I \) is the ratio calculated by the following formula:
$I = 10^w * \frac{t}{T}$

$$w = \begin{cases} 
2, & \text{when } t > 0.1T \text{ time,} \\
3, & \text{when } t > 0.5T \text{ time,} \\
4, & \text{when } t > 0.75T \text{ time,} \\
5, & \text{when } t > 0.9T \text{ time,} \\
6, & \text{when } t > 0.95T \text{ time.} 
\end{cases}$$  

(38)

(4) The antlion preys and rebuilds the trap stage, the position where the antlion eats the ants is the best position, and the antlion will reset the trap in this position, which can increase the probability of killing new prey. That is, when the fitness value of the ant is higher than that of the antlion, it means that the ant is killed by the antlion, and the formula is expressed as follows:

$$\text{antlion}^i_t = \text{ant}^i_t, \text{ if } f(\text{ant}^i_t) > f(\text{antlion}^i_t).$$  

(39)

To sum up, in the D2D direct connection mode, the fitness function of ALO is formula (9). In the D2D relay mode, the fitness function of ALO is formula (11), and the ALO algorithm has better global exploration ability.

2.3. Simulation Results and Analysis. The performance of the algorithm is verified by 1000 Monte Carlo experiments running on the MATLAB platform, and the average value of the final simulation results is taken. In a single-cell system, the cell radius is 500m, CU and the DUs are randomly distributed in it, and the initial position of the RU is also random, but will move at the speed of 2~3m/s based on the hybrid mobility model. It is assumed that the shadow fading of the D2D communication link and the cellular communication link in the system follows a log-normal distribution with a mean of 0 and a standard deviation of 10 dB and 12 dB, respectively, and the number of D2D user pairs is set to be consistent with the number of CUs, namely $d = \sqrt{N}$.

In order to better study the impact of swarm intelligence optimization algorithm on D2D communication performance, the following two algorithms are introduced as comparison algorithms.

2.3.1. Particle Swarm (PSO) Algorithm. A D2D power allocation strategy based on PSO is proposed, its original
strategy is introduced as a comparison algorithm, and the Hungarian algorithm is set to deal with the relay selection problem.

2.3.2. Whale (WOA) Algorithm. In the swarm intelligence optimization algorithm, the population size and the number of variables are the important algorithm parameters, which will affect the global optimization ability of the algorithm. Figure 1 presents a graph of the energy efficiency summation of D2D users as a change of the population size \( n \). Among them, \( d = 25 \) and \( P_{\text{max}} = 24 \text{dBm} \). It can be seen from the simulation diagram that the ALO, GWO, and PSO algorithms are not highly sensitive to the population size, that is, they can basically remain stable even when the population size is changed, thereby ensuring the efficiency of the algorithm. However, the MFO and WOA algorithms have requirements on the population size. The larger the population size, the better their optimization effect will be, which is determined by the nature of their algorithms. In the optimization results, the three algorithms of ALO, GWO, and MFO can always outperform the WOA and PSO algorithms, indicating that these three approximate optimization algorithms have stronger optimization ability.

Figure 2 presents a graph of D2D user energy efficiency summation as a change of the number of D2D user pairs (dimension) \( d \). Among them, \( n = 20 \) and \( P_{\text{max}} = 24 \text{dBm} \). It can be seen from the observation that with the increase of the number of D2D user pairs, the overall energy efficiency summation of the DUs in the system also increases. At the same time, the increase of the variable dimension also means that it will be more difficult to search for the global optimal solution, and the performance of the algorithm itself will be tested. Among them, the results of the four algorithms of ALO, GWO, WOA, and PSO are basically increasing steadily, but after the number of D2D user pairs exceeds 30, the upward trend of the MFO algorithm will gradually ease, even slightly lower than that of the WOA algorithm. This shows that when the number of variables \( d \) exceeds the population size \( n \) to a certain extent, the global optimization ability of the MFO algorithm will be limited, the efficiency of the algorithm will decrease, and it is easy to fall into the local extreme value.

Convergence is an important parameter used to measure the performance of the algorithm in swarm intelligence algorithms. The curve that defines the function changing with the number of iterations is called the convergence curve. From the convergence curve, the optimization ability and convergence speed of the algorithm can be obtained.

Figure 3 shows the convergence curves of these algorithms. As can be seen from the figure, the optimization ability of the PSO algorithm is the worst, and the convergence speed is relatively slow. Although the optimization ability of the WOA algorithm is slightly improved, it will fall into a local optimum in the early stage of optimization. The optimization speed of the MFO algorithm is the slowest, but the optimization result will be higher than that of the WOA algorithm. The GWO algorithm can quickly converge to the vicinity of the global optimal value, and the convergence accuracy is only slightly lower than that of the ALO algorithm, and its optimization ability is strong. Due to the random walk and roulette strategy, the ALO algorithm ensures its ability to explore the searchable space, so that it can jump out of the local optimum and continue to find the global optimum value, so that its final convergence accuracy can be slightly higher than that of the GWO algorithm. Therefore, it has the strongest optimization ability among the five algorithms.

According to the analysis of the above three simulation graphs, in general, the ALO algorithm can obtain better algorithm performance. Moreover, the nature of its own
The algorithm makes it possible to avoid the problem of stagnation in the local optimum in high dimensions, thus obtaining more stable algorithm performance. Figure 4 presents the CDF curve of the summed energy efficiency of D2D users in the system. It can be seen that the system performance of the ALO algorithm is the best.
Table 1: Evaluation of resource integration effect of AI English teaching resource information intelligent integration system based on multi-agent writing.

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Figure 5 presents a graph of the D2D user energy efficiency summation as a function of $P_{\text{max}}$. It can be seen from the simulation diagram that the three algorithms of ALO, GWO, and MFO are obviously better than WOA and PSO algorithms, and with the increase of $P_{\text{max}}$, the overall energy efficiency of DU in the system decreases gradually. Moreover, it can be seen from the figure that the PSO algorithm has the fastest decline, followed by the WOA and MFO algorithms, while the ALO and GWO algorithms have the slowest decline, and the curve is more gentle than the PSO algorithm. This is because the increase of $P_{\text{max}}$ will lead to a wider search space, that is, it will increase the difficulty of searching for the global optimal solution, and test the optimization ability of the algorithm, which also reflects the superiority of the ALO algorithm in global search ability. However, in this case, the PSO algorithm is more likely to fall into the local extreme points, resulting in a decrease in the convergence accuracy.

2.3.3. Intelligent Integration Method of AI English Teaching Resource Information under Multi-Agent Collaboration. In order to improve the intelligent integration effect of AI English teaching resource information, this article combines the algorithm of the second part with a multi-agent to construct a resource integration system.

The architecture of the teaching resource integration system is divided into presentation layer, service management layer, service layer, service component layer, data access layer, and data layer. The basic architecture of SDO is composed of data objects, data graphs, metadata, and data relay services. Metadata is briefly introduced in previous chapters and will not be discussed here. A data object is a component used to save data and is mainly composed of attributes of a data entity, and a data graph is a collection of multiple data objects responsible for changes to the data objects. The data relay service is used for the management and invocation of services in the interface. The AI English teaching resource integration system proposed in this article is shown in Figure 6.

The system architecture design should follow the SOA service architecture, and the architecture design is shown in Figure 7.

According to the test steps and test basis of the second part, this article simulates the resource integration effect of the AI English teaching resource information intelligent integration system based on multi-agent collaboration and obtains the results shown in Table 1 and Figure 8.

The above research shows that the AI English teaching resource information intelligent integration system based on multi-agent collaboration proposed in this study can play an important role in the English teaching resource information integration.

3. Conclusion

English information resources refer to information resources in the English domain. According to its carrier, it can be divided into information resources orally imparted by English producers, physical information resources, English
literature information resources preserved in traditional paper carriers, and English network information resources spread on the Internet. For English-speaking researchers, timely and comprehensive access to English-language information resources will help improve their scientific research level. Moreover, the timely acquisition of English policies and regulations and other information by English producers is conducive to reducing the problem of information asymmetry in English translation teaching, and to a certain extent, reducing the losses caused by English translation. This study builds an intelligent integration system of AI English teaching resources and information on the basis of multi-agent collaboration. The simulation experiment study shows that the AI English teaching resource information intelligent integration system proposed in this article can play an important role in the English teaching resource information integration.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare no competing interests.

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References