# Design of an Online Sharing System for Ancient Literature Based on Mobile Technology

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**Abstract—**At present, the study of ancient literature is gradually gaining attention but related knowledge still mostly exists offline without enough sharing online. In order to design an online sharing platform for ancient literature, an improved particle swarm optimization algorithm is used to form AAD-MOPSO based on cognitive radio architecture and multiple input multiple output and adaptive angular region partitioning. The improved algorithm is capable of adaptively and reasonably partitioning the channel in complex situations and avoiding the problem of local optimal solutions and over convergence, ensuring the balance of the number of particles in each region by angular partitioning, and balancing the population optimal solution and global optimal solution among each user target. In the simulation experiments, the sample targets are divided into two data sets equally and randomly, and each data set is divided into five groups and the test results and statistical averaging results of each group are recorded, and four other algorithms, namely PSO, MOPSO, logistics and K-means, are used for comparison. The experimental results show that the average accuracy rate of AAD-MOPSO algorithm is 88.05%, the average adaptation rate is 53.41%, and the average F1 value is 1.082, which are significantly higher than the other four algorithms, verifying the feasibility of the improved algorithm.

**Keywords—**particle swarm optimization algorithm, multiple-input multiple-output, cognitive radio networks, online shared systems

## 1 Introduction

With the current rapid development of society in terms of technology as well as economic, people's standard of living has increased significantly, at the same time, people's hobbies have gradually increased. The study of ancient literature is currently respected, and the demand for discussion and sharing platforms for related knowledge has increased [1]. There are currently more online sharing platforms related to ancient literature, but they generally have certain defects, such as slow information transmission, information loss, low accuracy of recommendations, etc. [2]. Meanwhile, the current online platforms take the majority of traditional algorithms, which are difficult to process complex situations [3]. In view of this, study uses an improved multi-objective particle swarm optimization algorithm for the system design of online sharing platform based on multiple input and multiple output channels and cognitive radio network architecture, with a view to the application of the improved algorithm to the online platform of ancient literature.

## 2 Related work

A number of domestic and foreign scholars have made studies on algorithm proposal and improvement for online sharing systems. Chen's team calculated the similarity among users by combining collaborative filtering algorithm with other algorithms, and calculated the similarity among users' calligraphy words and the main recommended calligraphy words based on the preliminary recommendation results to get the final recommendation results (Chen et al. Jiang's team proposed a slope-one algorithm based on the fusion of trusted data and user similarity, which calculates the similarity among users by selecting trusted data and adding this similarity to the weighting factor of the improved slope-one algorithm to obtain the final recommendation equation, and the experimental results proved that the algorithm performs more accurately than traditional algorithms. Li et al. proposed a personalized collaborative filtering recommendation algorithm with social information and dynamic time window, which assigns corresponding time weights to users' interests at different periods by dynamically adjusting the time window and introducing time function, and the experimental results show that the algorithm outperforms the traditional recommendation algorithm. (Li et al. Han et al. proposed an improved time-weighted algorithm based on small-batch K-means clustering, combining Pearson correlation coefficient and k-means algorithm and using the improved Mini-Batch K-Means algorithm to cluster sparse scoring matrices. they introduced Newton cooling time weighting to improve user similarity, and the experimental results showed that the algorithm's performance was better than others. Panda S K's team designed a normalized recommender to recommend personalized items to strict users. The algorithm determines the average user rating of each item, counts the number of users who purchase each item, and then uses min-max normalization to find the normalized number of users for each item. This model was tested and found to predict user ratings more accurately [8]. Zhang et al. designed a coverage based shared recommendation algorithm to provide personalized recommendations for new users. They reconstructed a decision class algorithm by detailed analysis of new user characteristics and used a coverage reduction algorithm based on coverage in a rough set to remove redundant candidates for new users. Test showed that the improved algorithm significantly outperformed the existing traditional algorithm [9].

Many studies have been conducted on particle swarm optimization algorithms. Guangcheng et al. designed an adaptive learning particle swarm optimization algorithm with different learning strategies to transform the path planning problem into a minimization multi-objective optimization problem. They used a new adaptive learning mechanism to improve the search capability of the particle swarm optimization algorithm. Experimental results show the feasibility and effectiveness of this method [10]. Fu et al. improved the particle swarm optimization algorithm to identify more complex and variable information and applied the improved algorithm to mining keywords. Qi et al. combined artificial neural network with particle swarm optimization algorithm to form a new model for predicting the strength of cement slurry filling, using factors such as tailings type, cement tailings ratio, solids content and maintenance time as key predictive information, and the results showed that the accuracy of the improved algorithm model was significantly improved [12]. Ishikawa proposed a coherence-based distributed particle swarm optimization algorithm with event-triggered communication for the nonconvex infinitesimal optimization problem. A multi-agent system is used in which each agent has multiple particles as estimated solutions to the global optimal solution and dynamically updates the positions of the particles by averaging the consistency over an auxiliary variable that accumulates past information about its own objective function. Experimental results show higher trigger accuracy for this communication system [13]. Wang H's team proposed a robust sparse recovery spatio-temporal adaptive processing algorithm based on particle swarm optimization to estimate the clutter spectrum results in the presence of large parameter errors for the problem of nonsmoothed clutter suppression. The results of simulation experiments show that this improved algorithm has better robustness [14].

From the above study, it can be seen that the particle swarm optimization algorithm has been successfully applied in various fields, but it is relatively little applied to the system design of online sharing platform, and the improvement of this algorithm is feasible. A particle swarm optimization algorithm based on CRN-MIMO with an adaptive region division table is used to realize the construction of an online sharing system for ancient literature.

## 3 Application of CRN-MIMO and AAD-MOPSO algorithms in shared systems

### 3.1 Application of CRN-MIMO technology in the design of shared platform systems

For learning and contributing to ancient literature, it is often necessary to design a sharing platform system where users can upload and download valid information related to ancient literature, exchange and discuss it. Since the platform system needs to process information in multiple ways and provide personalized services to users, it requires appropriate mobile technologies and information processing algorithms that can accurately and quickly process huge information flows. The framework diagram of the whole sharing system is shown in Figure 1.

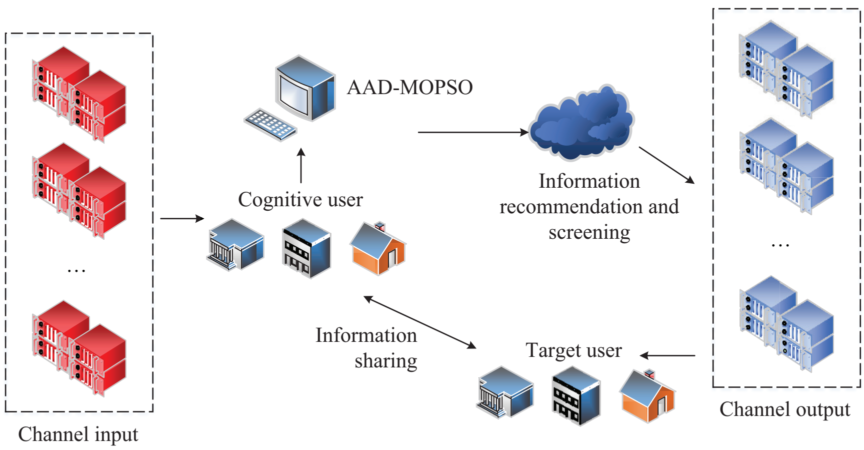


**Fig. 1.** Frame diagram of information sharing system

Multiple-Input Mutiple-Output (MIMO) wireless communication technology is a widely used mobile technology, which is derived from smart antenna technology and antenna diversity technology. Typically, MIMO uses multiple antenna units at both the transceiver and transmitter ends, which can effectively improve communication quality and speed. A MIMO unit is usually equipped with at least three transmit antennas and an equal number of receive antennas to obtain a higher spectral efficiency [15]. The basic schematic of MIMO is shown in Figure 2.

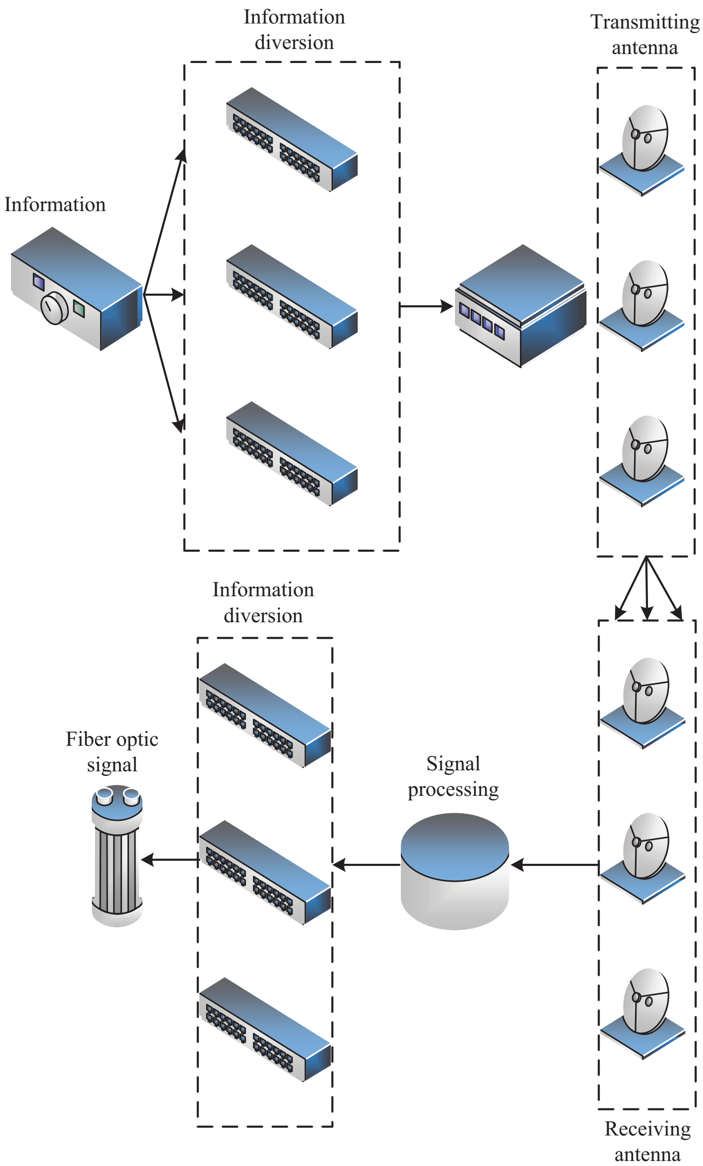


**Fig. 2.** MIMO communication schematic diagram

MIMO can make full use of space resources and exploit them, transforming the multipath propagation of the wireless channel into an advantageous factor for communication and using it, while significantly improving the spectral efficiency and system capacity in the system without increasing the transmit power and bandwidth. Since MIMO technology has various advantages such as high efficiency, space resources saving and wide range of applications, there are many related technology extensions. Under the condition of multiple channels, the Shannon formula for communication is shown in equation (1). In equation (1), $C$ represents the channel spatial rate, $W$ represents the RF bandwidth, $n$ is the equivalent channel parameter, $\sigma_i$ is the channel balance, $P_i$ is the received power of each channel, $N_i$ represents various types of noise such as thermal noise, blue noise, scatter, etc., and $I_i$ is various types of interference.

$$C = W \cdot \sum_{i=1}^{n} \log_2[1 + \frac{\sigma_i^2 P_i}{N_i + I_i}] \tag{1}$$

Suppose there is a MIMO model with $a$ transmitters and $b$ receivers, then there is a channel relationship as shown in equation (2). In equation (2), $x_i(t)$ is the transmit signal of transmitter $i$, $Y_j(t)$ is the receive signal of receiver $j$, $n_j(t)$ is the Gaussian white noise, and $h_{ji}$ is the corresponding channel frequency from the transmitter to the receiver.

$$\begin{cases} Y_j(t) = \sum_{i=1}^{a} h_{ji} x_i(t) + n_j(t) \\ i = 1, 2 \ldots a, j = 1, 2 \ldots, b \end{cases} \tag{2}$$

In matrix form, the channel response frequency is shown in equation (3).

$$H = \begin{bmatrix} h_{11}, \ldots, h_{1a} \\ \ldots \\ h_{b1}, \ldots, h_{ba} \end{bmatrix}_{a \times b} \tag{3}$$

Under the premise of Shannon's formula, for a given information transmission model, different channel capacities can be obtained based on different diversity sets, which are calculated as shown in Table 1.

**Table 1.** MIMO channel capacity formula under different diversity

| | | |
|---|---|---|
| SINGLE INPUT<br>SINGLE OUTPUT | No diversity, a = b = 1 | $C_{11} = W[\log 2(1 + \delta\chi^2)]$ |
| SINGLE INPUT<br>MULTIPLE OUTPUT | Receive diversity, b = 1 | $C_{1a} = W[\log 2(1 + \delta\chi a^2)]$ |
| MUTIPLE INPUT<br>SINGLE OUTPUT | Transmit diversity, a = 1 | $C_{b1} = W[\log 2(1 + \delta\chi a^2)]$ |
| MUTIPLE INPUT<br>MUTIPLE OUTPUT | Transmit receive diversity, a = b | $C_{xx} = W[\log 2(1 + \delta)HH^H]$ |

Cognitive Radio Network (CRN) is a network architecture based on Cognitive Radio (CR), whose core idea is to use the learning ability and environment awareness of machines to achieve spontaneous utilization of local resources. The core of the CRN architecture is the CR spectrum management technology. In CR spectrum management, a simplified cognitive cycle is formed by using the cognitive loop model, which interacts with the external environment to obtain external incentives and then enters the cognitive cycle. CR spectrum management consists of six processes: observation, orientation, planning, decision making, learning and execution. Based on the simplified cognitive cycle, CR spectrum management is divided into four modules, which are spectrum sensing technology module, spectrum analysis technology module, spectrum decision technology module, and spectrum movement technology module [16]. The basic cognitive loop of CRN architecture is shown in Figure 3.

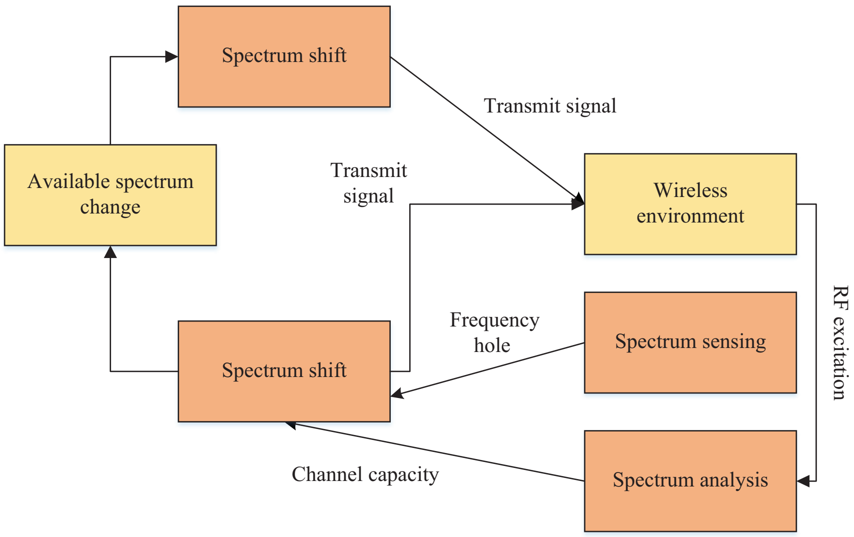


**Fig. 3.** Basic schematic diagram of cognitive ring

The combination of CRN and MIMO technology means the use of multiple input and multiple output methods to form a CR control channel, which is the CRN-MIMO technology. The most important function of CRN-MIMO is to input and output multiple channels for complex information when the user content is complex, and its downlink channel model is shown in Figure 4.

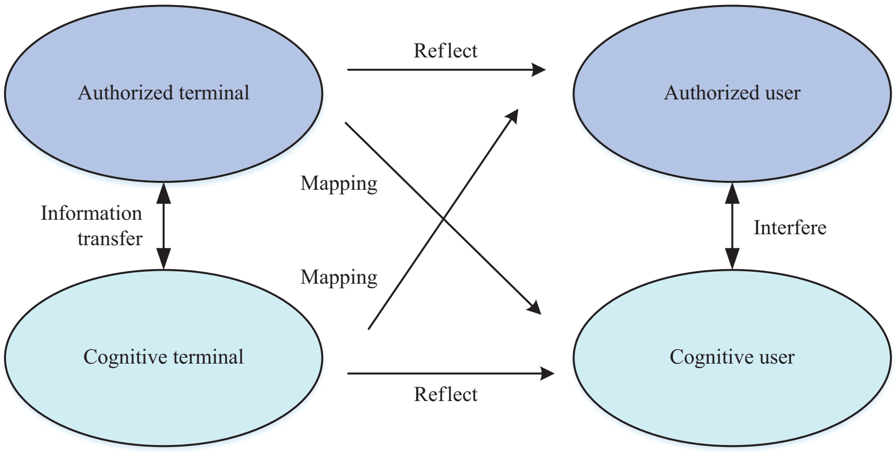


**Fig. 4.** Schematic diagram of CRN-MIMO system downlink channel model

The system capacity of CRN-MIMO is shown in equation (4). In equation (4), $W$ is the system bandwidth and $\frac{H_i^j \sum j(H_i^j)^H}{R_U + \sigma^2 I}$ is the expression of $SINR$.

$$C = \max \sum i[W \log 2 \det(I + \frac{H_i^j \sum j(H_i^j)^H}{R_U + \sigma^2 I})] \tag{4}$$

When the signal is independent and identically distributed Rayleigh channel, the transmitting and receiving volume of cognitive users are $n$, and the channel capacity is shown in equation (5) when $n$ is infinite.

$$C = n \log 2(1 + SINR) \tag{5}$$

### 3.2 Study on the application of MOPSO algorithm to online sharing system

In a CRN-MIMO system, it usually contains an authorized terminal and a cognitive terminal. At the same time, it contains multiple authorized users and cognitive users. Since the system generally adopts a communication mode in which authorized and cognitive users coexist, resulting in possible interference between users, CRN-MIMO needs to maximize the information transmission with a constrained total transmit power. In this case, the Particle Swarm Optimization (PSO) algorithm is used to maximize the information output while ensuring the accuracy of the information.

The PSO algorithm is a bionic algorithm in which the problem-solving process is analogous to birds' food searching process. There is an information interaction between individuals in the population and individuals, also between individuals and the optimal individual. This interaction guides the particles in the population to converge toward the optimal individual while preserving the information of individual diversity [17]. Therefore, in the decision space, the update of particles is obtained by combining the population history optimal particles with the individual history optimal particles. When the current velocity of a particle is v(T), its next moment velocity is v(T + 1), which is determined by both the current velocity, its own optimal position Pb(T) and the global optimal position GB(T). The particle moves from X(T) to X(T + 1) position. The diagram of the particle moving in the decision space is shown in Figure 5.

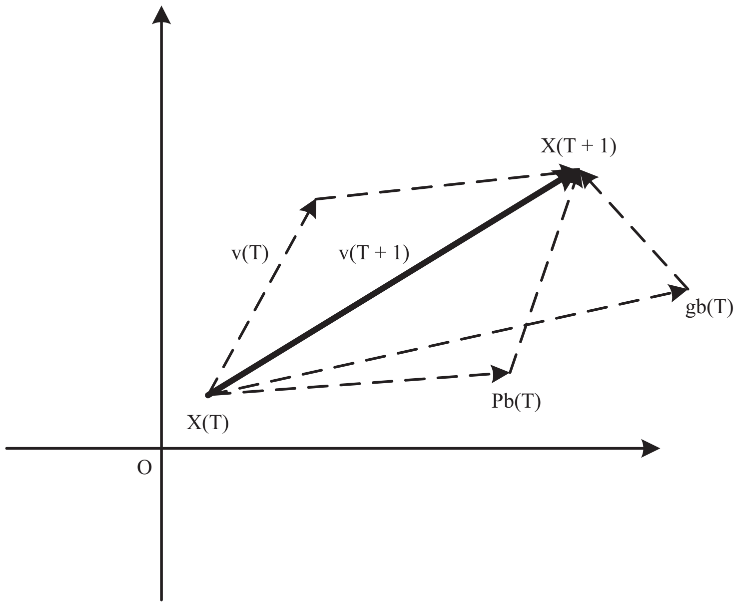


**Fig. 5.** Schematic diagram of particle movement in decision space

After getting the trajectory of the particles, PSO is optimized, the population is randomly initialized, the position and velocity of each particle in the population are initialized, after that the state of each particle is evaluated based on the fitness function, and the population optimal solution is selected from these particles. According to the PSO algorithm update equation, the position and velocity of the updated particles are obtained, after which the optimal solution of itself and the optimal solution of the population are updated. Finally, it is decided whether the solution of the current particle is superior to the previous optimal solution or the population optimal solution, and if it is superior to the most, leave the new solution. The update position equation of the particle swarm algorithm is shown in equation (6).

$$x_{r,d}(t+1) = x_{r,d}(t) + v_{r,d}(t) \tag{6}$$

In equation (6), $t$ is the number of iterations, $x_{r,d}$ denotes the position of particle $r$ in the population in dimension $d$, and $v_{r,d}$ denotes the velocity of particle $r$ in the population in dimension $d$. The update velocity formula of the particle swarm algorithm is shown in equation (7). In equation (7), $r_1$ and $r_2$ are two different random numbers distributed in the interval [0,1] to increase the randomness of the algorithm, $c_1$ and $c_2$ are acceleration constants to control the learning step, $px_{r,d}$ and $gx_{r,d}$ represent the historical individual optimal solution and population optimal solution, respectively, and $\omega$ represents the inertia weight to adjust the effect of the last velocity on the current velocity.

$$v_{r,d}(t+1) = \omega v_{r,d}(t) + c_1 r_1 (px_{r,d}(t) - x_{r,d}(t)) + c_2 r_2 (gx_{r,d}(t) - x_{r,d}(t)) \quad (7)$$

According to the equation, the current velocity of the particle is affected by the previous velocity, the current action of the particle incorporates the position and velocity of the historical optimum, and the population optimal solution is capable of information fusion through collaborative cooperation and knowledge sharing. Therefore, the PSO algorithm has certain adaptive performance and is suitable for finding the changing optimal solution in the dynamic model. The basic flow of PSO is shown in Figure 6.

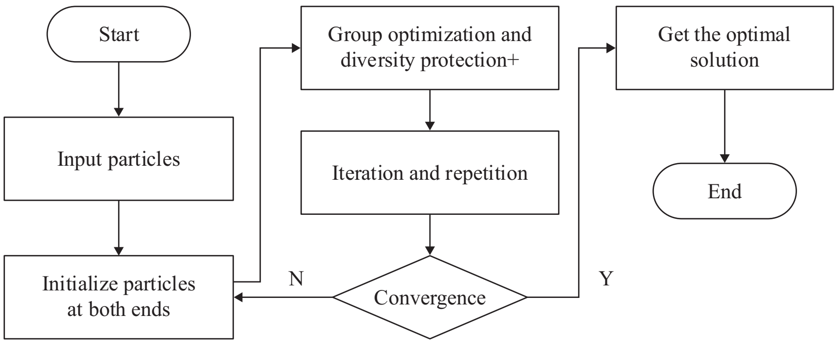


**Fig. 6.** Basic flow chart of PSO algorithm

Mutiple Objects Particle Swarm Optimization (MOPSO) is a typical particle swarm optimization algorithm, and unlike the conventional PSO, MOPSO is capable of optimizing multiple particle swarm objectives simultaneously. That is to say, considering both a single particle swarm and multiple particle swarms as a whole under which the optimal solution is derived [18]. The basic operations of MOPSO are shown in equations (8) and (9). In equations (8) and (9) $n$ denotes the number of targets.

$$x_n(t+1) = \sum_{n}^{i=1} x_i(t) + \sum_{n}^{i=1} v_i(t), i = 1, 2, \ldots, n \quad (8)$$

$$v_n(t+1) = \sum_{n}^{i=1} \omega v_i(t) + \sum_{n}^{i=1} c_n r_n (gx_i(t) - x_i(t)), i = 1, 2, \ldots, n \quad (9)$$

The advantages of MOPSO are the ability to solve problems in parallel fast and efficiently. However, MOPSO still has some problems, namely the deficiency of the optimal particle selection strategy and the tendency of particles to enter the local optimal solution, the balance problem of diversity and convergence [19]. In order to solve the main problems of MOPSO and to further optimize it, experiments were conducted using the Adaptive Angle Division-Mutiple Objects Particle Swarm Optimization (AAD-MOPSO) algorithm based on adaptive angle division.

AAD-MOPSO mainly focuses on maintaining the population diversity of the particle population and trying to avoid converging too early or falling into the local optimal solution, i.e., obtaining the global optimal solution with balanced diversity and convergence. In the beginning stage, the boundary particle information is fully utilized to enhance the exploration of the whole region, and the division angle is adaptively adjusted in the target space based on the number of particles, after which the optimal particles are selected according to the regional distribution of particles. For regions without particles, the development is facilitated by the guidance of particles in neighboring regions.

In the actual shared system design, there will be a large gap between multiple objective functions. To ensure the balance between the objectives, object value cannot be directly and simply superimposed, but need to normalize each objective value to obtain a more objective value. The normalization function $f_{normal}(x)$ of an individual $x$ is shown in equation (10).

$$f_{normal}(x) = \frac{f(x_n) - f_{\min}}{f_{\max} - f_{\min}}, n = 1, 2, \ldots, N \tag{10}$$

In equation (10), $f_{\max}$ and $f_{\min}$ denote the maximum and minimum values of the objective function for all individuals in the current population, respectively. After normalization, the range of values of all objectives is [0,1].

After the normalization process, in order to obtain a distribution of solutions with wider coverage and maintaining population diversity to ensure stable optimization, the boundary particle information needs to be fully utilized in the initialization stage, while the globally optimal particles need to guide the updates of other particles within the population to enhance the global search [20]. To prevent the lack of global exploration of the entire decision space due to excessive search of local regions, two extreme boundary particles with the maximum and minimum values of a certain target value are needed to guide the population update as the global optimal particles, respectively, i.e., the uniform initialization based on the guide of boundary particles.

In the initialization stage, the minimum value boundary particle of a certain target is used as the global optimal particle to guide the particle update. After updating $n_1$ generation, the particle returns to the initialization state, and the maximum boundary particle of the target is selected to guide the particle update, and continues to update $n_1$ generation. Similarly, the particle of the other boundary is updated $n_2$ generation, so as to improve the uniformity and overall coverage of the optimal solution set distribution in the target space, and maintain the population diversity. In order to keep the convergence level as consistent as possible and achieve uniformity, we set $n_1$ and $n_2$ to be equal and no greater than 5. The initialization state is saved, and the two extreme particles of a certain target are used as the optimal particles to continue guiding the update, which promotes the uniformity of particle distribution and makes the coverage more comprehensive.

Since the angle division in the target space is determined by the number of particles in the current external archive, and the number of particles in the external archive is small in the initial stage, the angle division of the target space needs to be adaptive according to the number of particles in the external archive, and the population individuals are guided to enhance the deep search in low-density regions to prevent the emergence of multiple particle-free region. The number of particles in the region grows as the number of iterations increases, and the conditions for adaptive region division are shown in equation (11).

$$\frac{(i-1)P}{i_{\max}} < P_{archive} \le \frac{iP}{i_{\max}} \tag{11}$$

In equation (11), $P$ is the maximum storage capacity of the external archive set, and $i_{\max}$ indicates the maximum number of divisions. Equation (12) needs to be satisfied when the number of partitioned areas is $D$. Suppose the initial number of divisions is 3 and the maximum storage capacity is set to 100. When the angle is greater than 30 degrees and not greater than 60 degrees, the number of divisions is adjusted to 9, and the angle is adjusted to 10 degrees and so on.

$$i_{\max} \le \log_D P \tag{12}$$

The target space is divided into at most 100 regions, which means the minimum angle of each region is 0.9 degrees. In order not to affect the convergence speed of the algorithm, two termination conditions of the algorithm iterations are set, when one of them is satisfied, the algorithm ends. Condition one is that there is at least one particle in each region, and condition two is that the number of iterations reaches 100 generations.

For optimal particle selection, particles from low-density regions are randomly selected as population optimal solutions to guide population renewal. After dividing the adaptive regions, the adjacent regions without particles are preferentially selected, and the particles in them are used as the population optimal solutions. To maintain the external archive set, when the number of particles reaches the upper limit, the excess particles are randomly removed so that at most one particle exists in each angle region.

To test the performance of the algorithms of the shared system, the target user samples were randomly divided equally into two test sets, each divided into five groups, and tested in the simulation system using AAD-MOPSO. To compare the results, PSO, MOPSO, logistic regression algorithm and K-means algorithm are compared in the simulation experiment, and the same test method is used.

## 4 Simulation experimental results and analysis

The time required to complete 100 iterations for each algorithm is shown in Figure 7. As seen in Figure 7, the time required for the iterations of the AAD-MOPSO algorithm is significantly lower than the other four algorithms, and the results for each of the two datasets are the lowest for the AAD-MOPSO algorithm. The average results for data set 1 of the AAD-MOPSO algorithm are 32.01 and 33.55, while the results for

PSO, MOPSO, logistics, and K-means are 43.25–44.36, 39.90–41.08, 40.92–40.58, and 40.34–41.13, respectively. According to the results of the significance analysis, the average results of AAD-MOPSO algorithm in both datasets are lower than the other four algorithms, indicating that AAD-MOPSO has a significant performance advantage in terms of iteration rate.

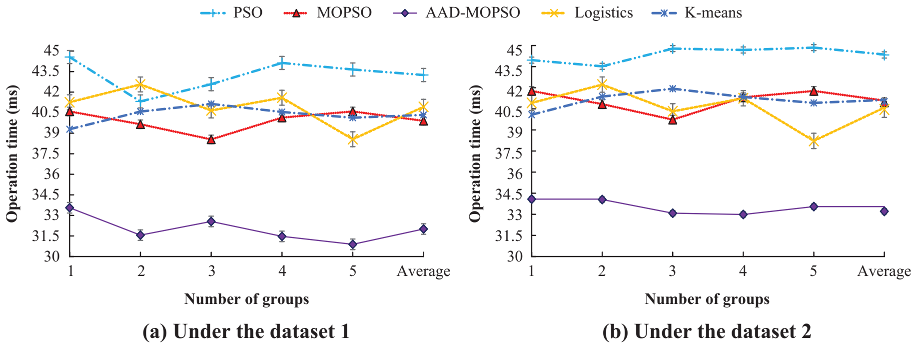


**Fig. 7.** Iteration time of five algorithms under two sets of data sets

The results of the accuracy test for each algorithm are shown in Figure 8. As seen in Figure 8, the accuracy of the AAD-MOPSO algorithm is significantly greater than PSO and MOPSO and greater than logistics and K-means in dataset 1. The accuracy of AAD-MOPSO is significantly greater than PSO, MOPSO and logistics and greater than K-means in dataset 2. Combining the average accuracies of the two datasets. PSO, MOPSO, AAD-MOPSO, logistics and K-means were 71.49%, 76.83%, 92.63%, 85.41% and 87.89% accurate, respectively. According to the analysis of the significance results, the accuracy of AAD-MOPSO is significantly higher than the three algorithms PSO, MOPSO and logistics, while there is no significance between the accuracy of AAD-MOPSO and that of K-means. The results indicate that the AAD-MOPSO algorithm has significantly better performance in obtaining the optimal solution.

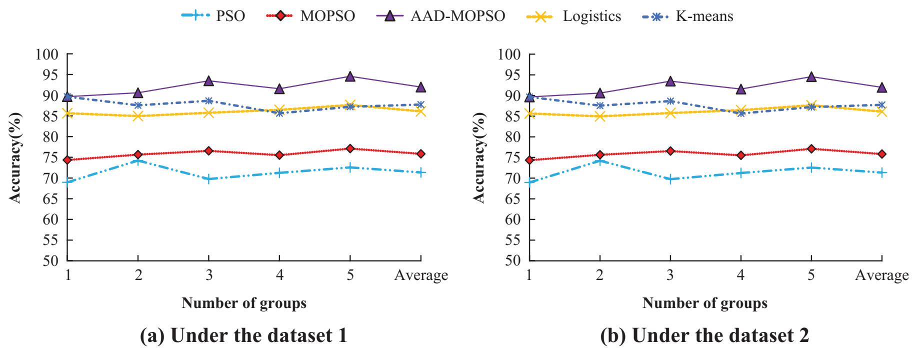


**Fig. 8.** Accuracy rate of five algorithms under two sets of data sets

The results of the recall test for each algorithm are shown in Figure 9. As can be seen from Figure 9, the K-means algorithm in the first group in dataset 1 has a higher recall than the AAD-MOPSO algorithm, while for the other groups in both datasets, AAD-MOPSO is significantly greater than the other four algorithms. The average recall of AAD-MOPSO in both datasets is 84.40%–84.30%, with an overall average recall of 84.35%, while the PSO, MOPSO, logistics and K-means have an overall average recall of 63.1%, 72.59%, 79.29% and 79.09%, respectively. Based on the results of the significance analysis, it is known that the recall rate of the AAD-MOPSO algorithm is significantly higher than the other four, indicating that AAD-MOPSO has a more superior performance in the ability to identify positive examples.

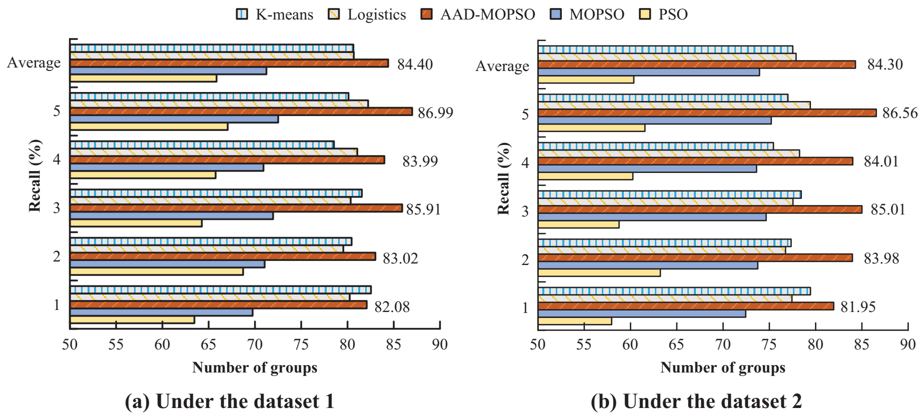


**Fig. 9.** Recall rate of five algorithms under two sets of data sets

The results of the precision test for each algorithm are shown in Figure 10. From Figure 10, it can be seen that the accuracy rates of AAD-MOPSO in both datasets are significantly greater than those of PSO and MOPSO, where the accuracy rates of AAD-MOPSO in dataset 1 are higher than those of logistics and K-means but not significantly. The accuracy rates of AAD-MOPSO in dataset 2 are significantly higher than those of the other four algorithms. After averaging the two datasets to obtain the overall average accuracy rate and performing significance analysis, the results for PSO, MOPSO, AAD-MOPSO, logistics and K-means were 66.8%, 76.28%, 88.05%, 82.99% and 82.79%, respectively, which showed that the accuracy rate of AAD-MOPSO was significantly higher than the other four algorithms. It indicates that the performance of AAD-MOPSO in balancing between the global optimal solution and the individual optimal solution is significantly better than the other algorithms.

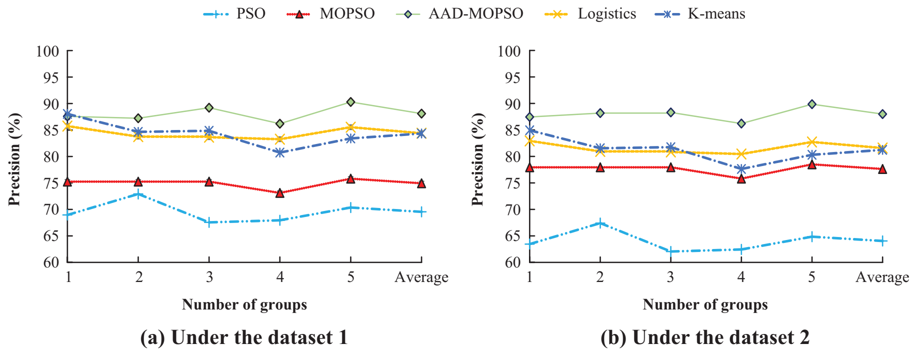


**Fig. 10.** Recall rate of five algorithms under two sets of data sets

The results of the adaption test for each algorithm are shown in Figure 11. From Figure 11, it can be seen that the adaptation rate of the AAD-MOPSO algorithm is significantly higher than that of the PSO, MOPSO, and K-means algorithms, and higher than that of the logistics algorithm. The average adaptation rate of AAD-MOPSO is 52.40% and 54.42% for the two data sets, respectively, and according to the analysis of the significance results, it is known that the adaptation rate of AAD-MOPSO is significantly different from that of the PSO, MOPSO, and K-means algorithms, while it is not significantly different from that of the logistics algorithm. PSO, MOPSO and K-means are significantly different from the three algorithms, while there is no significant difference with logistics, indicating that the performance of the improved algorithm in adaptive adjustment is significantly better than that of the algorithm before improvement, and it has some advantages in individual optimal solutions.

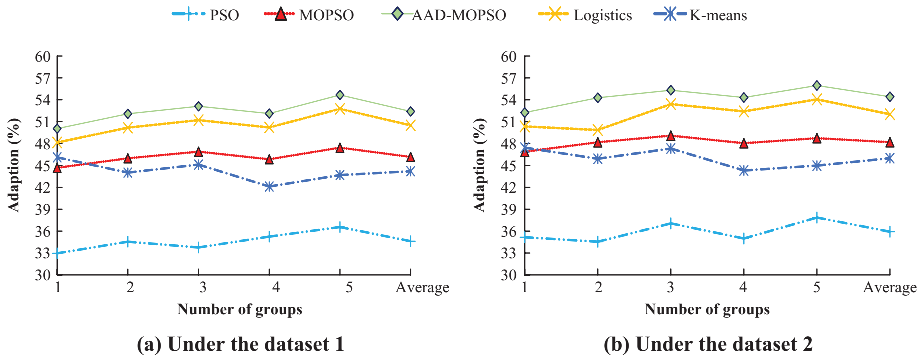


**Fig. 11.** Adaption rate of five algorithms under two sets of data sets

The results of the F1 test for each algorithm are shown in Figure 12. As seen in Figure 12, the F1 values of the AAD-MOPSO algorithm are significantly higher than those of PSO and MOPSO in all two data sets. It is not significantly different from those of the logistics and K-means algorithms in data set 1, and significantly higher than those of the two algorithms in data set 2. Combining the average results of the two datasets for significance analysis, it is known that the F1 of the AAD-MOPSO algorithm is significantly higher than the other four algorithms. That is to say, AAD-MOPSO has a significant performance advantage in terms of comprehensive performance as well as feasibility.

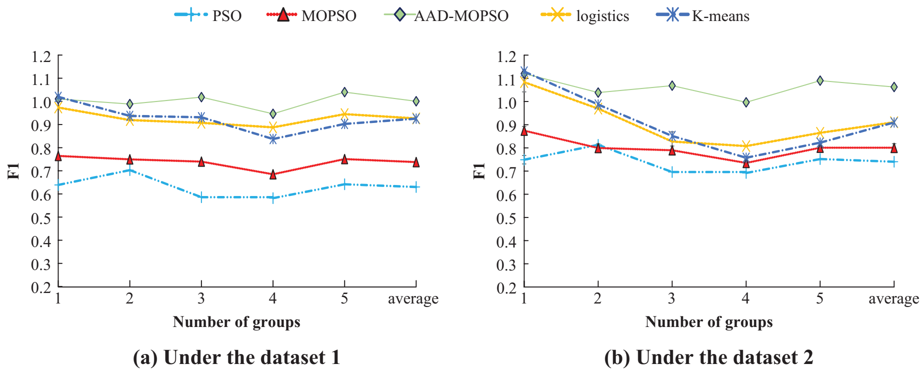


**Fig. 12.** Comprehensive evaluation index (F1) of five algorithms under two sets of data sets

## 5 Conclusion

To design an online communication and sharing platform of ancient literature, the experiment uses the CRN-MIMO architecture as the foundation of information delivery, and adopts a multi-objective particle swarm optimization algorithm based on adaptive angular region division, namely AAD-MOPSO to enhance information input and output as well as screening and recommendation. The study compares the improved algorithm with four other algorithms at the same time. The experimental results show that the average accuracy of AAD-MOPSO is 92.63%, the average accuracy is 88.05%, the average adaptation rate is 53.41%, and the average F1 value is 1.082, and all these values are better than the other four algorithms of PSO, MOPSO, logistics and K-means. Most of the data of the improved algorithm are significantly higher than the other four algorithms. The results show that the AAD-MOPSO algorithm has significant performance advantages over the traditional algorithm before improvement, including iteration rate, global optimal solution, operational adaptability, and the balance between global and individual optimality. Although the research has achieved certain results, the total number of samples selected during the experiments is small and the experimental results lack universality, which is the main direction to be optimized in further research in the future.

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