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Multi-Objective Optimization for Human Resource Allocation Using Reinforcement Learning and Enhanced Cuckoo Search Algorithm

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In today's fiercely competitive business environment, enterprises are increasingly relying on efficient human resource allocation to improve operational efficiency and reduce operating costs. To better allocate human resources, this study proposes a multi-objective imperialist competition algorithm that integrates optimized Cuckoo Search algorithm and reinforcement learning, and creates a new human resource allocation optimization model. The new model can effectively explore solution space and adapt to talent allocation under different conditions by simulating the parasitic behavior of cuckoos and competition between empires. The results indicated that the new model performed the best when the population size was 50, the number of ruling countries was 40, the task exchange probability was 0.1, the resource replacement probability was 0.05, the colonial power coefficient was 0.2, and the number of colonies was 2. The average ideal distance of the mixed integer non-derivative optimization algorithm was 0.71, the diffusion of non-dominated solutions was 0.73, the momentum volume was 0.77, and the average response time of the solution was 2.43s. The indicators corresponding to the new model were 0.69, 0.76, 0.78, and 0.51s, respectively. Compared with the mixed integer non-derivative optimization algorithm, the new model reduced the average ideal distance by 0.02 and improved the diffusion of non-dominated solutions by 0.03. In addition, the momentum volume increased by 0.01, the average response time for solving was 0.51s, and the speed increased by 1.92s, all of which were better than the comparative algorithms. The average score of the new model after allocating human resources was above 9. The data showed that the new model had good convergence, fast solving speed, stable and high-quality results, and could effectively allocate talents. The research model has important practical significance for improving the efficiency of human resource scheduling and decision-making quality.

Povzetek: Raziskava predstavi optimizacijski model IDCS-OMOICA za razporejanje kadrov, ki s kombinacijo okrepljenega iskanja kukavičjih gnezd in učenja s krepitvijo izboljša učinkovitost, odzivnost in raznolikost rešitev.

1 Introduction

In the contemporary epoch of the knowledge economy, knowledge and information have emerged as the paramount factors of production. The core competitiveness of enterprises is increasingly contingent on the knowledge, skills, and innovation abilities of their employees [1]. With the continuous advancement of globalization and technological innovation, enterprises are facing more intense market competition and constantly changing business needs [2]. On the one hand, enterprises need to ensure sufficient talent support for key positions to maintain daily operations and achieve short-term goals [3]. On the other hand, companies also need to invest in the long-term development of their employees to build sustainable competitive advantages [4]. Traditional Human Resources (HR) management methods are no longer able to meet the needs of modern enterprises. Enterprises must find new ways to attract, retain, and develop talent while ensuring that the allocation of HRs maximizes work efficiency and employee satisfaction [5]. Based on this, how to effectively manage and configure HR to quickly adapt to market changes and meet corporate strategic goals has become a common focus of attention for enterprise managers and scholars [6]. Seifi H et al. proposed a Grey Wolf Optimization (GWO) algorithm based on Sugeno fuzzy inference model to optimize the allocation of HR in small and medium-sized enterprises. This method significantly improved model performance in larger B100 and B200 datasets, and could obtain the best allocation results and solutions [7]. Dabirian S et al. proposed a dynamic model to effectively allocate labor to solve the problem of HR allocation in construction projects. This model could accurately estimate labor demand and effectively allocate it to ensure timely supply and distribution of project labor [8]. Rodgers W et al. constructed a throughput model framework to address ethical decision-making in HR management, describing the algorithm's individual decision-making process in the HR management environment. The new model demonstrated how perception, judgment, and information usage affect strategy selection, and identified how adopting certain ethical decision-making algorithm paths can support different strategies [9]. Waldkirch M et al. proposed a clustering-based incremental association rule mining algorithm to improve the efficiency of data mining and incorporated it into the HR management system of universities. The experimental results showed that the algorithm achieved visualization of HR information system data and could effectively mine large-scale databases [10]. Tarafdar et al. proposed a theoretical framework to explore the role interaction between humans and algorithms in algorithmic work, thereby addressing human-machine interaction in task allocation. Algorithms lacked transparency in task allocation, task tracking, and performance evaluation. They provide a new perspective for understanding algorithm management in HR allocation and emphasizing the need to focus on human experience and feedback when designing algorithms [11]. Park H et al. proposed a stakeholder centered solution to alleviate the tense relationship between artificial intelligence and stakeholders in HR management. This plan has successfully eased these tensions by focusing on stakeholders and promoting harmony among various stakeholders [12]. Nikzad et al. proposed a two-stage random mixed integer model that considers multiple factors simultaneously to better allocate HR in the healthcare system, considering the uncertainty of travel and service times. The test results have demonstrated the algorithm's ability to solve large instances [13].

Table 1: Summary and comparison table of various studies.

Study	Method	Advantages and Limitations
Seifi H et al. [7]	GWO based on Sugeno Fuzzy Inference Model	The model performance significantly improves in larger B100 and B200 datasets, achieving optimal allocation results and solutions.
Dabirian S et al. [8]	Dynamic Model	Accurately estimates labor demand and effectively allocates resources to ensure timely labor supply and distribution in construction projects.
Rodgers W et al. [9]	Throughput Model Framework	Demonstrates how perception, judgment, and information use influence strategy selection and identifies how certain ethical decision-making algorithm paths support different strategies.
Waldkirch et al. [10]	Clustering-based Incremental Association Rule Mining Algorithm	Achieves visualization of human resource information system data and effectively mines large-scale databases.
Tarafdar M et al. [11]	Theoretical Framework	Explores the role interaction between humans and algorithms in algorithmic work, emphasizing the need to consider human experience and feedback in algorithm design.
Park H et al. [12]	Stakeholder-Centric Solution	Promotes harmony among various stakeholders, alleviating tensions surrounding algorithmic evaluation in human resource management.
Nikzad E et al. [13]	Two-Stage Stochastic Mixed-Integer Model	Considers uncertainties in travel and service times, with experimental results proving the algorithm's capability to solve large-scale instances.
Proposed in This Study	IDCS-OMOICA	Exhibits good convergence, fast solving speed, stable and high-quality results, effectively allocating talent. The average ideal distance, diffusion of non dominated solutions, momentum volume, and average response time for solving are 0.69, 0.76, 0.78, and 0.51 seconds, respectively

Compared with other results, the proposed method provides more indicators to quantify the performance of the algorithm, making it easier to evaluate and compare (Table 1). The solving speed is 0.51s, suitable for fast response scenarios such as real-time HR allocation. The findings are consistent and of superior quality, demonstrating the capacity to produce varied and high-quality solution sets. This property is of particular significance for multi-objective optimization problems, as it overcomes the challenge of unstable results that may be present in alternative methods. This method not only performs well in theory but also has important practical application significance, which can effectively improve the efficiency of HR scheduling and decision quality. Although those proposed algorithms have achieved certain results in their respective applications, there are still some shortcomings. For example, the GWO algorithm may face slow convergence speed and local optima when dealing with complex multi-objective problems, and its prediction accuracy may be affected by data quality. Although dynamic models can effectively allocate labor, they may not be flexible enough to respond to rapidly changing demands. The Cuckoo

Search (CS) algorithm has strong global search capability. To address these issues and allocate HR efficiently and quickly, this study combines the Improved Discrete Cuckoo Search (IDCS) algorithm and the Optimized Multi-Objective Imperialist Competition Algorithm (OMOICA) based on Reinforcement Learning (RL) optimization to form a new HR configuration optimization model (IDCS-OMOICA). The innovation lies in adjusting search strategies in real-time through RL mechanisms to respond to changes in project requirements and HR conditions. The search parameters are automatically adjusted through Q-Learning to reduce human intervention and improve the robustness and adaptability of the model. Efficient global search is achieved through Lévy flight and random walk mechanisms. The local optimization is carried out using Q-Learning and Empire Competition mechanisms to improve computational speed. Through the above improvement methods, the GWO algorithm has been studied to solve the problems of slow convergence speed, local optima, and prediction accuracy affected by data quality when dealing with complex multi-objective problems. At the same time, it can also adapt to the flexibility of rapidly changing demands. The corresponding HR Scheduling Management System (HRSMS) has been developed, and the algorithm results have been transformed into practical and operable tools, providing technical support for enterprises. Its six-layer architecture design ensures the efficiency, security, and scalability of the system.

2 Method

2.1 Fusion of IDCS Algorithm and OMOICA

In today's rapidly developing industrial and social environment, HR Configuration Optimization (HRCO) has become a key factor in improving organizational efficiency and reducing costs [14]. Especially in multi-project environments, how to effectively schedule limited HR to meet the specific needs of each project has become a complex and challenging problem. Some algorithms, such as genetic algorithms, have complex operations such as encoding, crossover, and mutation, with multiple parameter settings, requiring a large amount of computing resources and time. The problem of HR allocation has a lot of data and many constraints, making it difficult for these algorithms to process efficiently. Traditional algorithms such as gradient descent rely on gradient information and are prone to getting stuck in local optima. HR allocation problems have multi-modal characteristics, making it difficult for these algorithms to globally search for optimal solutions. The CS algorithm has strong global search capabilities and can explore the vast solution space of HR configuration. RL algorithms can refine and optimize strategies through trial-and-error learning in this solution space to adapt to changes in project requirements and uncertainties in the work environment. For example, a software company is facing an urgent project with a sudden increase in demand, while some employees are absent from training. RL considers this change as a new state and dynamically adjusts configuration strategies based on historical data and real-time feedback, such as project progress, employee skills, and availability. RL interacts with the environment (project and HRs system), with the agent (scheduling system) selecting actions (assigning tasks), and the environment providing rewards (project completion on time, cost control). Intelligent agents learn optimal strategies, adjust configurations in real-time, ensure smooth project progress, and efficiently allocate HRs. However, traditional CS algorithms may encounter slow convergence speed and be prone to getting stuck in local optima when dealing with complex HR configuration problems. Based on this, to effectively allocate HRs in complex situations and meet the needs of various departments, this study optimizes the CS algorithm. The structure of the IDCS algorithm is shown in Figure 1.

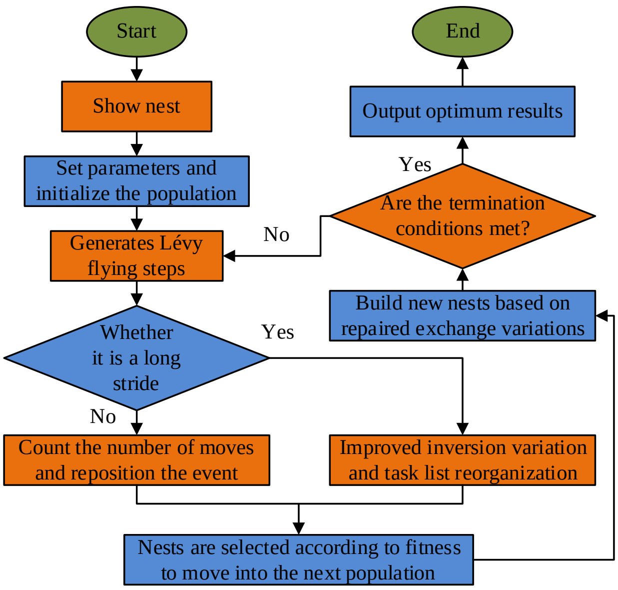

Figure 1: IDCS algorithm structure diagram.

In Figure 1, the IDCS algorithm is mainly used to solve complex optimization problems, such as resource-constrained multi-project scheduling problems. IDCS explores the solution space and finds the optimal solution through Lévy flight and random walk mechanism. The Lévy Flight Step Size (LFSS) has a heavy tail characteristic, which means there is a high probability of large step jumps occurring during the search process. This approach enables the algorithm to rapidly explore a more extensive search space in a short period, thereby avoiding the potential stagnation in local optima. Additionally, it facilitates a more comprehensive consideration of the allocation of HRs from a macro perspective, ultimately leading to the identification of a more optimal overall configuration. Random walk is a mathematical statistical model of irregular motion, where neighboring points are randomly selected for comparison each time. It enables the algorithm to perform detailed local searches in relatively concentrated areas, fine-tune and optimize existing HR allocation schemes, and improve the accuracy and adaptability of the schemes. The structure of IDCS mainly includes steps such as initializing the population, evaluating fitness, Lévy flight updating the nest, random walk generating new nests, and selecting the next generation population. In the initialization phase, the algorithm generates an initial population, with each individual representing a solution. In the fitness evaluation stage, the algorithm calculates the fitness value of each individual, which is their quality as a solution. Lévy flight is a key component of IDCS. IDCS updates the solution by simulating the behavior of cuckoos searching for new nests [15]. In this process, the algorithm uses an Lévy distribution to generate step sizes, allowing the algorithm to conduct detailed searches in local areas as well as wide area explorations on a global scale. The LFSS is calculated using the Mantegna algorithm, and the calculation formula is shown in equation (1) [16].

$$L = \frac{|x_i|}{\mu}\left(\frac{\Gamma(1+\lambda)\sin(\pi\lambda/2)}{\Gamma((1+\lambda)/2)}\lambda^{-\lambda}\right)^{1/\lambda} \quad (1)$$

In equation (1), L represents LFSS. Γ is the gamma function. λ is a parameter of the step size distribution. x_i and μ are variables in the algorithm. When LFSS is between [0,2], small step length movements are performed, and the relationship between the number of movements and the step length is shown in equation (2) [17].

$$\begin{cases} M_s = \left\lceil \frac{L \cdot D}{3} \right\rceil, L \in [0,1] \\ M_s = \left\lceil \frac{(L+1) \cdot D}{3} \right\rceil, L \in (1,2] \end{cases} \quad (2)$$

In equation (2), M_s is the number of small step movements. D is the dimension of the solution space. $\lceil \; \rceil$ is rounded up. When LFSS is greater than 2, large step jumps are executed. The number of jumps is determined by the step size, and the calculation method is shown in equation (3).

$$M_l = \left\lfloor \frac{L}{2} \right\rfloor \quad (3)$$

In equation (3), M_l is the number of jumps, and $\lfloor \; \rfloor$ is rounded down. In the random walk stage, the algorithm eliminates solutions with poor fitness with a certain probability and generates new solutions to replace them. Finally, the algorithm selects the best individual based on fitness to enter the next generation, iterating continuously until the termination condition is met, such as reaching a predetermined number of iterations or the quality of the solution reaching a certain threshold. The formula for adaptively adjusting the elimination probability based on individual fitness values is shown in equation (4) [18].

$$p_a = 1 - e^{-(f(x_i)/\bar{f})^{-1.1}} \quad (4)$$

In equation (4), p_a is the elimination probability. $f(x_i)$ is an individual's fitness value. $\bar{f}$ is the average fitness value in the population. The IDCS algorithm can effectively balance global search capability and local search accuracy through iterative search, thereby improving the probability of finding the global optimal solution. In multi-objective problems, it is necessary to adopt an algorithm with multi-objective processing capability and integrate it with IDCS [19]. HR allocation needs to take into account multiple objectives such as cost, efficiency, and employee satisfaction. OMOICA, through strategies such as Pareto dominance, can simultaneously optimize multiple conflicting objectives, find an equilibrium solution set, and meet comprehensive optimization needs. However, other algorithms such as IDCS are relatively weak in multi-objective coordination. The problem of HR allocation is complex and ever-changing, with flexible OMOICA parameters that can adapt to different scales and constraints, and quickly respond to changes in enterprise needs. Other multi-objective algorithms, such as multi-objective genetic algorithms, have complex parameter settings, relatively poor adaptability, and are difficult to maintain stable performance in changing scenarios. Therefore, this study uses the OMOICA to search for targets with multiple constraints to meet the needs of HRCO, and the solving method is Pareto. Figure 2 shows the Pareto solution process.

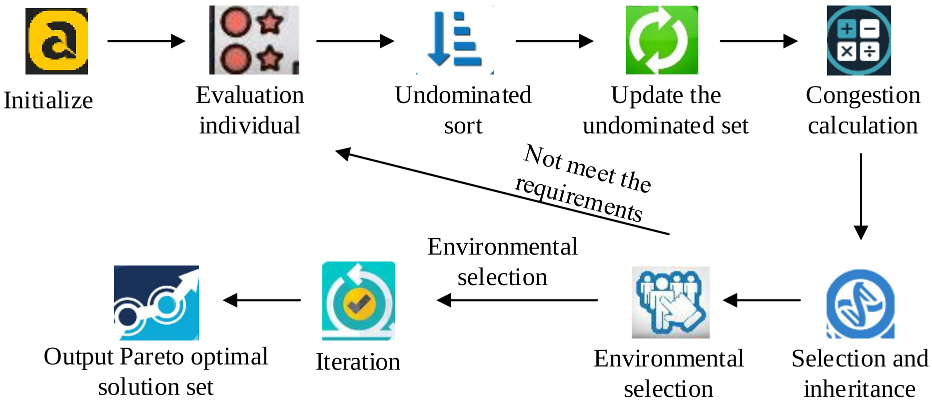

Figure 2: Pareto solution process diagram.

In Figure 2, the process first initializes the solution set, evaluates the objective function values of the solutions, and performs non-dominated sorting to determine the Pareto dominance relationship of the solutions. After updating the non dominated set, the crowding degree is calculated to maintain the diversity of solutions, followed by genetic operations and environmental selection to determine the next generation solution set. These steps are iterated until the Pareto optimal solution set is found. The definition of Pareto solution is shown in equation (5) [20].

$$\begin{cases} f_i(x_1) \le f_i(x_2) \\ f_j(x_1) < f_j(x_2) \end{cases} \quad (5)$$

In equation (5), x_1 and x_2 represent the solution values. If for all objective functions f_i, equation $f_i(x_1) \le f_i(x_2)$ is satisfied, and there is at least one objective function f_j that satisfies $f_j(x_1) < f_j(x_2)$, then it is called x_1 dominating x_2. The multi-objective optimization problem can be expressed as minimizing the objective function vector, as shown in equation (6).

$$F(x) = [f_1(x), f_2(x), ..., f_m(x)] \quad (6)$$

In equation (6), $F(x)$ is a set of vectors, f_m is a different objective function, and x is the solution value. The definition of feasible region constraints for multi-objective optimization problems is shown in equation (7).

$$D' = \{x \mid g_i'(x) \ge 0, i \in [1, M'], h_j'(x) = 0, j \in [1, L']\} \quad (7)$$

In equation (7), D' is the feasible region. $g_i'(x)$ is the i-th inequality constraint function. M' is the total number of inequality constraints. $h_j'(x)$ is the j-th equality constraint function. L' is the total number of equality constraints. i and j are indices that respectively traverse all inequalities and equality constraints. The crowding distance is used to measure the distribution density of solutions on the Pareto front, as shown in equation (8) [21].

$$d(x^*) = \sum_{k=1}^{m} \frac{f_k(x^*) - f_k^{\min}}{f_k^{\max} - f_k^{\min}} \quad (8)$$

In equation (8), $d(x^*)$ is the crowding distance. $f_k^{\max}$ and $f_k^{\min}$ are the maximum and minimum values of the k-th objective function. x^* is the distribution term. Figure 3 shows the structure of the OMOICA.

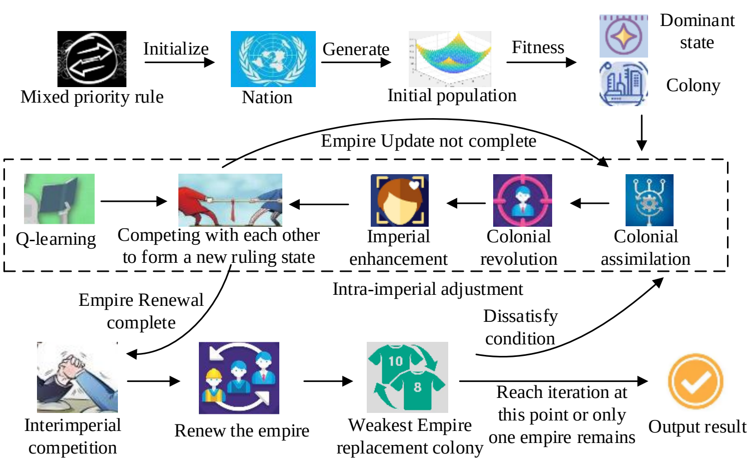

Figure 3: OMOICA structure diagram

In Figure 3, OMOICA is optimized using Q-Learning method (QRL). OMOICA first generates an initial population through mixed priority rules, dividing "countries" into "ruling countries" and "colonies", and enhancing the diversity and quality of solutions through assimilation and competition mechanisms. This process introduces a mechanism of learning from non-dominated solutions within external archives to enhance the diversity of the population. Next, the algorithm introduces QRL to optimize the search strategy. When the preset number of iterations is reached or all countries are unified into one empire, the algorithm terminates and outputs the result. The process of integrating IDCS and OMOICA mainly combines the efficient search capability of IDCS with the multi-objective optimization and RL capability of OMOICA. IDCS explores the solution space through Lévy flight and random walk, while OMOICA utilizes QRL and IDCS optimization strategies [22]. After the fusion of the two, the IDCS-OMOICA algorithm can find the optimal HR configuration solution that meets the requirements in a dynamic environment.

2.2 Construction of HR configuration optimization model

After successfully integrating IDCS and OMOICA, this study will construct an efficient IDCS-OMOICA model. This model will integrate the advantages of the aforementioned hybrid algorithms to adapt to the ever-changing industrial environment and achieve optimal resource allocation. The optimization problem of the IDCS-OMOICA model is to maximize organizational efficiency and employee satisfaction while meeting project requirements, employee skill matching, time constraints, cost-effectiveness, and other constraints. The purpose is to optimize the overall performance of the organization, fully realize the individual value of employees, and minimize the company's costs (including training time costs and employee turnover costs). The construction of IDCS-OMOICA model is a complex process that requires consideration of multiple factors, including project requirements, employee skills, time constraints, and cost-effectiveness. The structure of the IDCS-OMOICA model is shown in Figure 4.

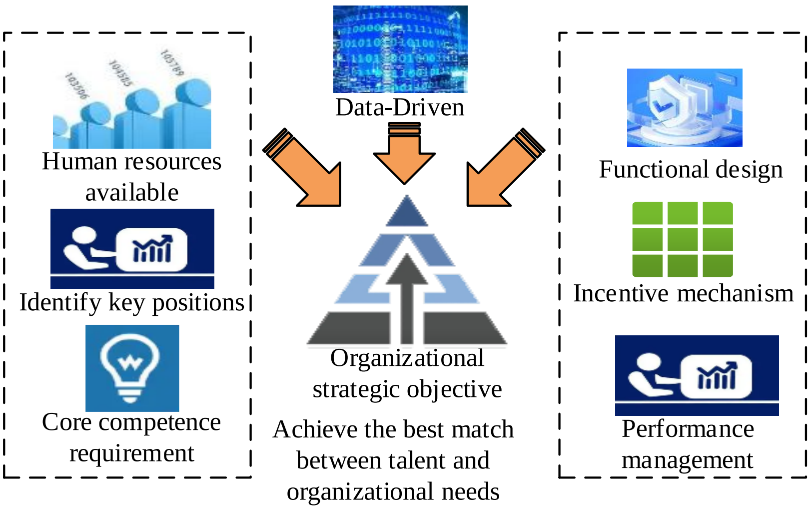

Figure 4: IDCS-OMOICA model structure diagram.

In Figure 4, the IDCS-OMOICA model is a systematic framework aimed at improving organizational effectiveness and employee satisfaction. This model focuses on organizational strategic goals and identifies key positions and core competency requirements by analyzing and evaluating the existing HR situation. It optimizes talent recruitment, training, promotion, and retention strategies through data-driven methods that combine market trends, employee performance and potential assessments, as well as organizational culture and values. The data-driven part is mainly achieved by integrating IDCS and OMOICA algorithms. The data used in "data-driven" include internal data such as employee performance, skill evaluation, project progress, as well as external data such as market trends, industry standards, etc. The data sources are extensive, covering enterprise information systems, market research, public datasets, etc. When enterprises compete for HR allocation, standardization cost is commonly used as one of the allocation indicators. Departments with low standardization costs have high resource utilization efficiency and require fewer personnel. Departments with high costs face significant cost pressures, so priority should be given to support allocation to ensure smooth project progress. The calculation of standardization cost is shown in equation (9).

$$C_n = c_n - \max_i \{c_i\} \quad (9)$$

In equation (9), C_n is the standardization cost of the n-th department or project group. c_n is the cost of key positions in the n-th core employee. $\max_i\{c_i\}$ is the maximum cost of key positions among all core employees. The expression for the relative power of core employees is shown in equation (10).

$$p_n = \frac{C_n}{\sum_{i=1}^{N_{\text{imp}}} C_i} \quad (10)$$

In equation (10), p_n is the relative power of the n-th core employee. N_{imp} is the total number of key positions. The equation for assigning new employees is shown in equation (11).

$$N_{C_n} = \text{round}\{p_n \times N_{\text{col}}\} \quad (11)$$

In equation (11), NC_n is the number of employees assigned to the n-th team or department that can be managed and trained, which is determined based on the relative strength p_n of the department or project group. N_{col} is the total number of available new employees. round is a rounding function used to calculate the number of new employees. $p_n \times N_{col}$ is converted to the nearest integer. The total cost calculation of the department or project team is shown in equation (12).

$$T_{C\cdot n} = f(imp_n) + \xi \times \frac{\sum_{i=1}^{N_{C_n}} f(col_i)}{N_{C_{in}}} \quad (12)$$

In equation (12), $T_{C\cdot n}$ is the total cost of the department or project team. $f(imp_n)$ is a core employee. $f(col_i)$ is a new employee. ξ is the weight coefficient. The search process for finding the optimal allocation plan is optimized using the RL method. The status represents the current allocation of HRs, including employee skills, project requirements, department status, etc. Action is a resource allocation decision based on the current state, such as assigning new employees, adjusting employee positions, etc. Rewards reflect the effectiveness of allocation strategies and are related to indicators such as project completion, employee satisfaction, cost-effectiveness, etc. The state value function is shown in equation (13).

$$V_\pi(s) = E_\pi[G_t \mid S_t = s] \quad (13)$$

In equation (13), $V_\pi(s)$ is the expected return following strategy π in state s. E_π is the expected value of a performance metric when following a specific strategy π. G_t is the total return starting from time t. S_t is the state of time. The action value function is shown in equation (14).

$$Q_\pi(s,a) = E_\pi[G_t \mid S_t = s, A_t = a] \quad (14)$$

In equation (14), $Q_\pi(s,a)$ is the expected reward for executing action a in state s and following strategy π. A_t is the action of time t. The Bellman Expectation Equation (BEE) can transform dynamic optimization problems into simple sub-problems, describing the relationship between the current state value and the next state value, and is a core concept in RL. BEE can provide a mathematical foundation for solving optimal strategies, helping to find strategies that maximize cumulative rewards by evaluating state value and action value. The state value function is shown in equation (15).

$$\begin{cases} V_\pi^{'}(s) = \sum_{a\in A} \pi(a \mid s) Q_\pi(s,a) \\ Q_\pi^{'}(s,a) = r(s,a) + \gamma \sum_{s'\in S} P(s' \mid s,a) V_\pi^{'}(s') \end{cases} \quad (15)$$

In equation (15), s' and $Q_\pi^{'}(s,a)$ are the state value function and action value function of the BEE, and $r(s,a)$ is the immediate reward for performing action a in state s. γ is the discount factor. $P(s' \mid s,a)$ is the transition probability from executing action a in state s to state s'. When a plan loses all new employees, the plan is abandoned, and ultimately, there is only one optimal HR allocation plan left, at which point the algorithm terminates. The IDCS-OMOICA model also involves redesigning workflows and responsibilities to ensure that employees can unleash their maximum potential. In addition, the model also includes continuous improvement of incentive mechanisms and performance management systems to achieve the best match between talent and organizational needs. Optimizing incentive mechanisms includes linking performance results with salary, promotion, and training to meet employees' material and spiritual needs. For example, companies can establish honors such as Outstanding Employee Awards and Team Awards to stimulate employees' sense of honor and belonging. Establishing an open and inclusive corporate culture can increase employee engagement and satisfaction. The optimization of performance management system includes clarifying goals, setting indicators, adopting diversified assessment methods, strengthening communication and feedback, continuous improvement, etc., to improve the operational efficiency and core competitiveness of enterprises. To facilitate HR scheduling management, this study establishes an HRSMS based on the IDCS-OMOICA model, and its system architecture is shown in Figure 5.

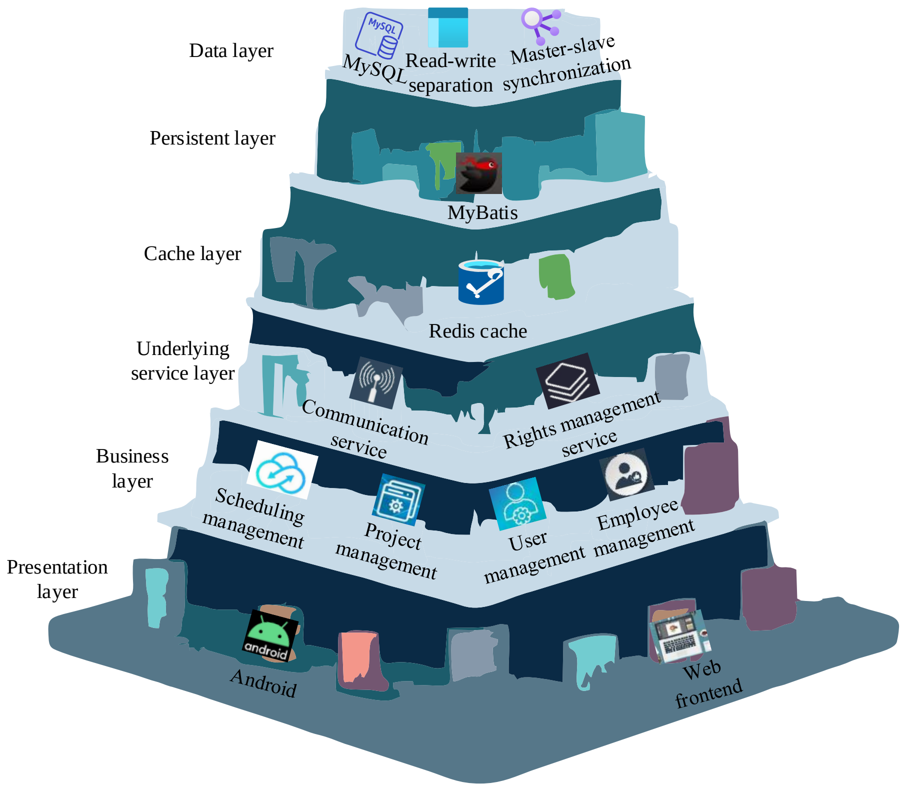

Figure 5: HR scheduling management system architecture diagram.

In Figure 5, HRSMS is built on top of a six-layer architecture, with the top layer being the user interface for web and mobile devices, used to display information and receive user operations. The business logic layer includes key functions such as user management, employee information, project data, and scheduling instructions. The scheduling management module in the business logic layer includes the IDCS-OMOICA model, which is the most core technical part of the entire system. The IDCS-OMOICA model analyzes HR data and allocates personnel based on user needs to derive HR allocation plans. The basic service layer provides permission verification and message services to ensure data security and timely communication. The caching layer utilizes Redis technology to optimize data access speed. The persistence layer works together with MySQL database through MyBatis to manage data storage and retrieval. The bottom data layer is mainly responsible for maintaining and processing data. The entire architecture aims to ensure the efficiency, security, and scalability of the system. The entire function of HRSMS is shown in Figure 6.

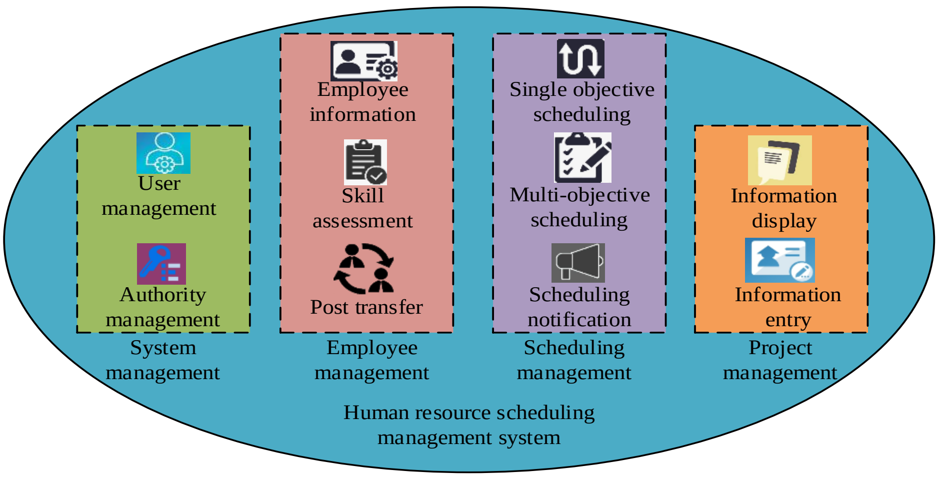

Figure 6: Function structure diagram of HRSMS.

The structure of Figure 6 highlights the main responsibilities and interactions of each module. The system management module is responsible for configuring users and permissions to ensure data security and operational compliance. The employee management module provides employee information and skill assessment to assist in job adjustments. The project management module is responsible for displaying and entering project data, allowing users to have a clear understanding of tasks and resource requirements. The core scheduling management module integrates multiple optimization algorithms to solve complex HR scheduling problems, and displays results through intuitive tables and Gantt charts, combined with message push functions to ensure real-time updates of scheduling information. These four modules together form a complete functional system aimed at improving HR scheduling efficiency and decision quality.

3 Result

3.1 Analysis of optimal parameter settings for IDCS-OMOICA

The experimental results obtained by IDCS-OMOICA are closely related to the configuration of algorithm parameters. This study sets the Population Size (PS) for algorithm parameter configuration at five levels: 50, 100, 150, 200, and 250. There are five options for the Number Of Ruling States (NORS): 5, 10, 20, 30, and 40. The Task Switching Probability (TSP) has five gradients of 0.1, 0.2, 0.4, 0.5, 0.6, and 0.7. The Resource Replacement Probability (RRP) is divided into five levels: 0.05, 0.25, 0.45, 0.55, and 0.65. The colonial power coefficient ξ has five scales of 0.1, 0.2, 0.3, 0.4, 0.5, and 0.7. The number of colonies N_{col} ranges from 1 to 5 in five stages. For the convenience of chart drawing, the above parameters are uniformly numbered from 1 to 5. The algorithm learning rate is 0.1 and the discount factor is 0.5. These parameters together form the basis for algorithm optimization. These parameter ranges are determined based on practical experience and can cover common application scenarios and problem scales. Choosing these parameter ranges can adapt to problems of different complexities. For example, larger population sizes and more ruling countries are suitable for complex problems, while smaller values are suitable for simpler problems. Conducting experiments within these parameter ranges can quickly find the optimal or approximate optimal solution while avoiding excessive computational costs. PS represents the number of individuals in the initial population of the algorithm. Each individual represents a possible solution. NORS represents the number of excellent solutions in the Imperial Competition algorithm. TSP represents the probability of an algorithm switching from one task to another during execution. RRP represents the probability of replacing solutions with poor fitness during the random walk stage of the algorithm. In the course of experimental analysis of HR scheduling problems, the objective is to reduce environmental interference, ensure the accuracy and reliability of results, and maximize the algorithm's optimal performance. To this end, the experimental platform parameters are set as listed in Table 2.

Table 2: Parameters of the experimental platform.

Operating system	Ubuntu Server 20.04 LTS 64-bit
RAM	16GB
CPU	Quad-core AMD EPYC 7401P 2.0GHz
Database	MySQL-8.0.34
Cache	Memcached-1.6.9
Deploying container engines	Kubernetes-1.20.0
Background development framework	Quarkus-1.12.0
Front-end development framework	React-17.0.2
Css preprocessor	Sass-1.32.8
Database management framework	MyBatis
Message push middleware	RabbitMQ-3.9.10 (Web) Firebase Cloud Messaging (Android)

The performance evaluation criteria for algorithms are Mean Ideal Distance (MID), Spread of Non-dominated Solutions (SNS), and Hyper Volume (HV). MID is a measure of the gap between HR allocation plans and ideal states. A low MID value indicates that the plan is close to ideal, resource allocation is reasonable, and employee and organizational goals are highly matched. SNS is a diversity indicator for evaluating HR allocation plans. A high SNS value means that the solution is evenly distributed and can cover multiple demand scenarios, improving the organization's ability to respond to changes. HV reflects the overall quality and scope of HR allocation plans. A high HV value indicates that the solution set covers a wide range and can optimize multiple objectives simultaneously, such as cost and efficiency. These performance indicators have been normalized. Figure 7 shows the performance indicators of the IDCS-OMOICA under different parameters.

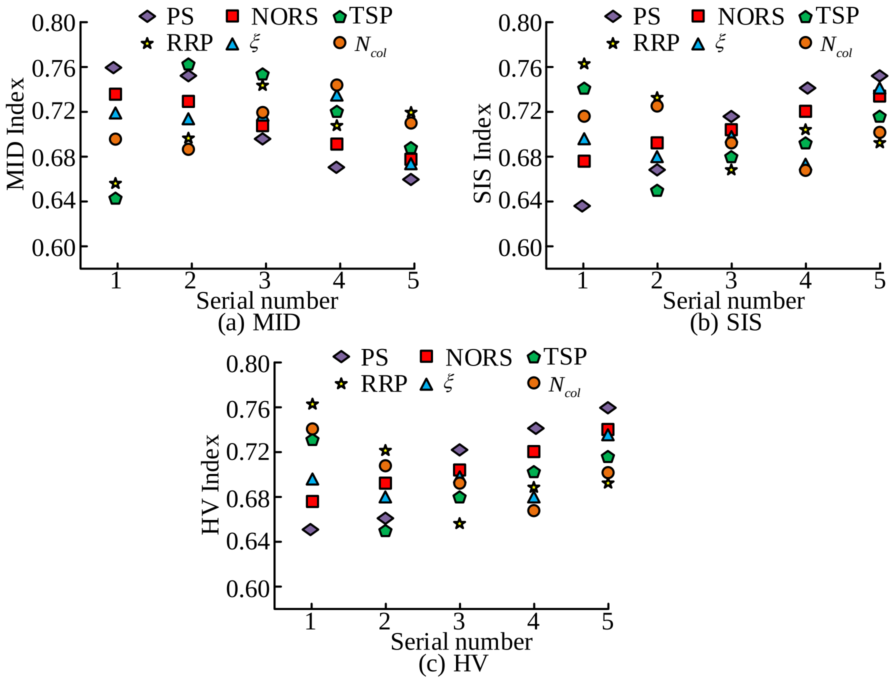

Figure 7: Test results of MID, SIS, and HV Performance indicators of IDCS-OMOICA under sequence number: 1-5.

In Figure 7 (a), taking the minimum MID value as the optimal criterion, when the PS of IDCS-OMOICA is 50, NORS is 40, TSP is 0.1, RRP is 0.05, ξ is 0.2, and N_{col} is 2, the MID values are 0.65, 0.66, 0.64, 0.66, 0.67, and 0.68. Low MID values help improve employee satisfaction and organizational performance, reducing resource waste. In Figure 7 (b), the algorithm parameters at the maximum SIS value are PS=50, NORS=40, TSP=0.1, RRP=0.05, ξ =0.2, and N_{col} =2. High SIS values can enhance organizational flexibility and innovation capabilities, adapting to changing environments. In Figure 7 (c), the algorithm parameters are also consistent with the maximum SIS value at the maximum HV value. High HV values can enhance an organization's comprehensive competitiveness under multiple objectives and achieve balanced development. Therefore, PS=50, NORS=40, TSP=0.1, RRP=0.05, ξ =0.2, and N_{col} =2 are the optimal parameter values for the IDCS-OMOICA. Under this parameter condition, the MID, SNS, and HV performance indicators of IDCS-OMOICA during training and testing are shown in Figure 8 after 400 iterations.

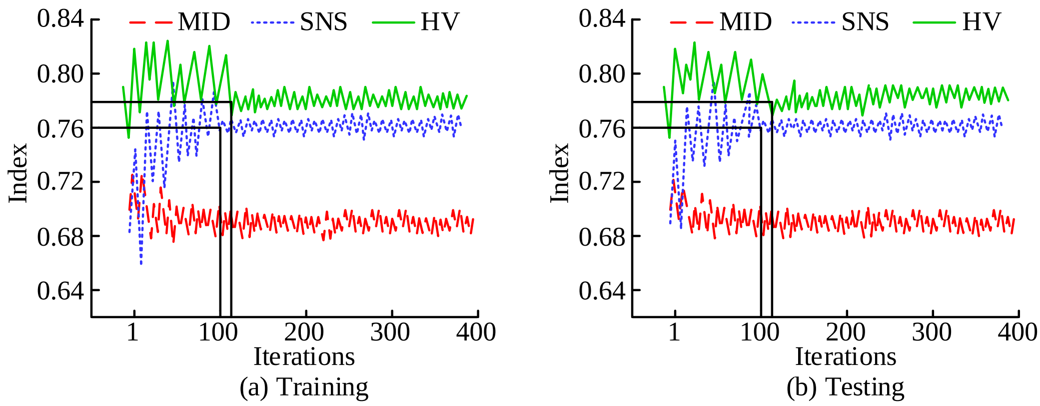

Figure 8: Comparison results of MID, SNS, and HV performance of IDCS-OMOICA during training and testing.

In Figure 8 (a), during the testing process, the MID index of IDCS-OMOICA tends to stabilize throughout the iteration, indicating that the overall solution of the algorithm is almost the same as the optimal solution. The

SNS and HV indicators tend to stabilize around 100 and 110 iterations, and eventually stabilize around 0.76 and 0.78. In Figure 8 (b), during practical application, IDCS-OMOICA exhibits a state that is basically consistent with the training process. The initial solutions to algorithms are usually randomly generated, and the quality of these solutions varies greatly, resulting in significant fluctuations in the objective function values during the initial iteration. MID stability is indicative of HR allocation that approaches optimal levels, with resources allocated in a suitable manner and employees aligned with organizational goals. This, in turn, fosters enhanced employee satisfaction and improved organizational performance. SNS is stable and high, which means that the configuration scheme is evenly distributed, covering multiple scenarios, enhancing organizational flexibility and innovation, and adapting to market changes. HV is stable and high, representing a wide range of configuration options that can consider multiple objectives such as cost and efficiency, and enhance the overall competitiveness of the organization for optimization. Therefore, the algorithm has good convergence effect, and the solution obtained under the set optimal algorithm parameters has high practicality, approaching the ideal state.

3.2 Comparative analysis of IDCS-OMOICA model performance

To further analyze the HR configuration performance of the IDCS-OMOICA model, this study compares the Constrained Evolutionary Algorithm with Dual Populations (CAEAD) and the Mixed-Integer Stochastic Optimization-Non-smooth Optimization by Mesh Adaptive Direct Search (MISO-NOMAD) algorithms. The CAEAD algorithm can effectively handle complex constraints in multi-objective optimization problems and is suitable for scenarios involving multiple constraints (such as cost, skill matching, project requirements, etc.) in HR allocation. The MISO-NOMAD algorithm is specifically designed to handle mixed integer optimization problems and is suitable for scenarios involving discrete decision variables (such as employee allocation) and continuous decision variables (such as cost and efficiency) in HR allocation. The comparison of MID, SNS, and HV indicators of each algorithm during the experimental process at iteration 400 is shown in Figure 9.

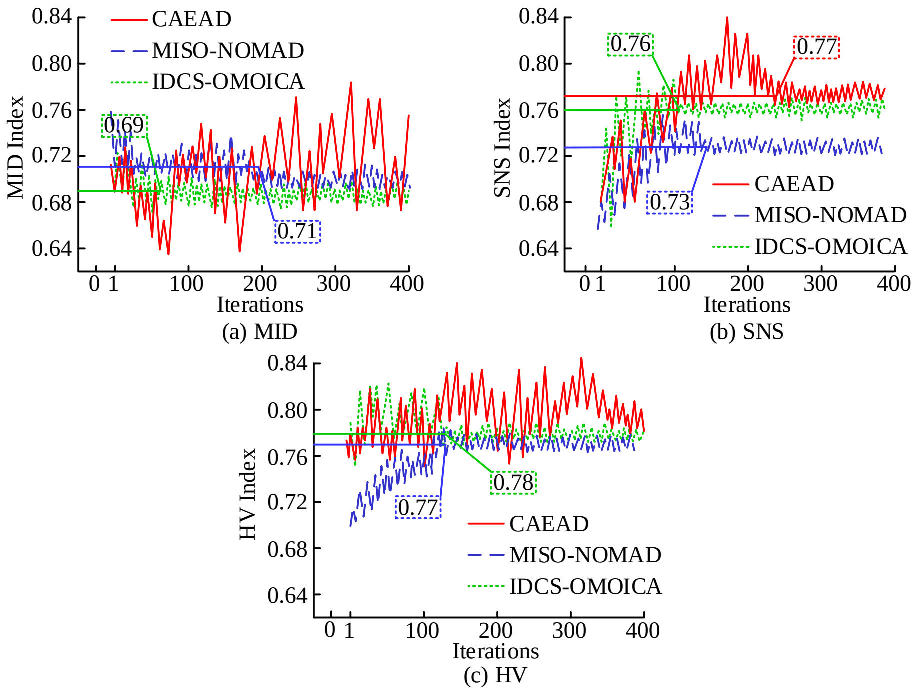

Figure 9: Test results of MID, SNS and HV indexes of each algorithm during 400 iterations.

In Figure 9 (a), the MID value of CAEAD is relatively high, but it is unstable throughout the entire iteration process. The MID value of MISO-NOMAD stabilizes around 0.71 when the iteration reaches around 190. IDCS-OMOICA remains relatively stable throughout the entire iteration, with an average MID value of 0.69, showing the best performance. In Figure 9 (b), the SNS values of CAEAD, MISO-NOMAD, and IDCS-OMOICA remain stable around 0.77, 0.73, and 0.76 at iterations 230, 130, and 100. Although the SNS value of CAEAD algorithm is relatively high after stabilization, it is not much different from the IDCS-OMOICA model, and the convergence speed is too slow. In Figure 9 (c), the HV value of CAEAD fluctuates significantly during the iteration process. The HV values of MISO-NOMAD and IDCS-OMOICA remain stable around 0.77 and 0.78 at iterations of 130 and 110. Overall, influenced by the Lévy flight strategy, the

IDCS-OMOICA model can converge faster and reach a stable state among all algorithms, and all indicators are superior to the compared algorithms. Compared with the MISO-NOMAD algorithm, the MID value of IDCS-OMOICA decreases by 0.02, the SNS value increases by 0.03, and the HV value increases by 0.01. Table 3 shows the actual performance of each model in the optimization of HR allocation in five project teams of a certain company.

Table 3: The performance of each model in real cases.

Case	IDCS-OMOICA			MISO-NOMAD			CAEAD		
/	MID	SNS	HV	MID	SNS	HV	MID	SNS	HV
1	0.66	0.77	0.78	0.69	0.71	0.74	0.35	0.61	0.60
2	0.64	0.76	0.77	0.71	0.69	0.75	0.87	0.62	0.58
3	0.65	0.78	0.75	0.71	0.71	0.76	0.54	0.69	0.55
4	0.65	0.79	0.76	0.69	0.68	0.74	0.36	0.61	0.57
5	0.63	0.77	0.78	0.73	0.70	0.76	0.74	0.71	0.59

To conduct a statistical analysis of the differences in the data in Table 3 and calculate the *P*-value, the study uses the One-Way ANOVA method to compare whether there are significant differences in the means of three or more groups of data. The study uses the Python's scipy stats library to calculate the F-value and *P*-value of analysis of variance. The final results showed that the *P*-values of MID, SNS, and HV are 0.0013, 0.0456, and 0.0012, respectively, all less than 0.05, indicating significant differences in the mean values of the three models in various indicators. In Table 3, IDCS-OMOICA demonstrates good performance in all cases. Its MID value is generally better than the comparison algorithm, which means that the solution obtained by this model is closer to the ideal solution. A lower MID value represents that the model can achieve more ideal arrangements in HR allocation, ensuring that employees are closely aligned with organizational goals. In terms of SNS, IDCS-OMOICA also performs well in most cases, demonstrating the diversity of its solutions. A higher SNS value indicates that the model can adjust flexible solutions in dynamic environments to meet diverse scene requirements. In terms of HV indicators, the performance of the model is particularly outstanding in cases 1 and 5, indicating that its solution set occupies a large volume in multidimensional space, that is, the model has high precision and accuracy. A higher HV value highlights the efficiency of the model in balancing multiple objectives, such as cost and efficiency, thereby enhancing the overall competitiveness of the organization. Therefore, the IDCS-OMOICA model has demonstrated good optimization capabilities and universality in practical cases. Figure 10 shows the personnel fit and response time of HR allocation schemes obtained by various algorithms on these instances.

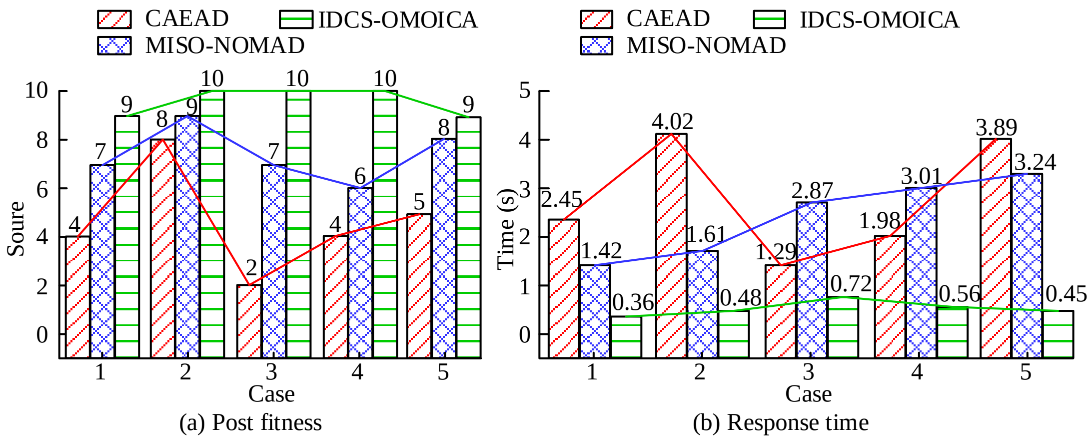

Figure 10: Comparison results of fitness and algorithm response time of various algorithms for HR allocation in practical cases.

In Figure 10 (a), the adaptability is evaluated on a scale of 1-10, with higher scores indicating that employees who have undergone HRCO are more suitable for their respective positions. The source of fitness score is a comprehensive evaluation of employees' performance in their positions, including multiple dimensions such as skill matching, job performance, task completion quality, team collaboration ability, and the fit between personal career development and the position. The data are collected through questionnaire surveys, performance evaluations, and feedback from colleagues and superiors. The data analysis models are used for quantitative scoring to obtain a fitness score ranging from 1 to 10. Influenced by the BEE, the IDCS-OMOICA model scores above 9 points on all instances, making it the highest scoring algorithm among all algorithms. In Figure 10 (b), the response time solved by CAEAD is very unstable. This is because CAAAD algorithm requires frequent adjustment of the solution structure when dealing with complex constraints in multi-objective optimization problems, which increases the computational complexity and uncertainty of response time. The average response time solved by the IDCS-OMOICA model is 0.51s, which is 1.92s faster than the MISO-NOMAD algorithm (2.43s). In summary, the IDCS-OMOICA model can achieve good results in optimizing HR configuration and help enterprises better apply talent. This model has a fast response time, can quickly obtain results, and has strong practicality. A short response time indicates the ability to quickly solve problems, reduce computational resource consumption, and improve overall efficiency. Faster response time can significantly improve user experience, reduce waiting time, and increase user satisfaction. High personnel adaptability indicates good solution performance. The experimental results indicate that the IDCS-OMOICA model can efficiently allocate HRs.

4 Discussion

In the era of knowledge economy, enterprises are facing fierce market competition and constantly changing business demands. Traditional HR management methods are no longer sufficient to meet the needs of modern enterprises. Enterprises need new methods for management to ensure that the allocation of HRs can maximize work efficiency and employee satisfaction. Based on this, this study proposes an IDCS-OMOICA model, aiming to effectively manage and allocate HRs, enabling them to quickly adapt to market changes and meet corporate strategic goals. The experimental results showed that the IDCS-OMOICA model outperformed the comparative CAEAD and MISO-NOMAD in performance indicators such as MID, SNS, and HV. Specifically, the average MID value of the IDCS-OMOICA model was 0.69, the SNS value stabilized around 0.76 at 100 iterations, and the HV value stabilized around 0.78 at 110 iterations. The stability and superiority of these indicators suggested that the IDCS-OMOICA model would rapidly converge and attain a stable state, producing diverse and high-quality solution sets. This was of particular importance for multi-objective optimization problems. Compared with the research of Seifi H et al. [7], the IDCS-OMOICA model not only performs well on large datasets but also has advantages in multi-objective optimization. The GWO algorithm based on Sugeno fuzzy inference model proposed by Seifi H et al. may face slow convergence speed and local optima when dealing with complex multi-objective problems. The IDCS-OMOICA model effectively avoids these problems through Lévy flight and random walk mechanisms, improving the algorithm's global search capability and resolution quality. As the size of the dataset increases, the model can adapt to more complex scenarios by adjusting parameters and optimizing algorithms, ensuring effective allocation of HRs in multi-project environments. Small and medium-sized enterprises often face challenges of limited resources and talent loss. Through efficient allocation of HRs, they can maximize production efficiency, reduce operating costs, and improve employee satisfaction, thereby enhancing their market competitiveness. In addition, technology companies and the healthcare industry can also utilize this model to optimize HR allocation in response to rapidly changing market demands and complex project management.

5 Conclusion

To solve the HRCO problem, this study proposed a fusion algorithm, IDCS-OMOICA, and established a corresponding model. The IDCS-OMOICA model effectively explored and adapted to dynamic environments by simulating the parasitic behavior of cuckoos and competition between empires. In the experiment, the SNS index of the IDCS-OMOICA model remained stable around 0.76 at iteration 100, and the HV index remained stable around 0.78 at iteration 110. This model outperformed the comparison algorithms in performance indicators such as MID, SNS, and HV. Compared with the MISO-NOMAD, its MID value decreased by 0.02, SNS value increased by 0.03, and HV value increased by 0.01. The average response time solved by this model was 0.51s, which was 1.92s faster than MISO-NOMAD. In summary, the IDCS-OMOICA model has good optimization ability and universality in practical applications. The research model has fast convergence and high solution quality. However, due to the involvement of RL and imperialist competition mechanisms, it may consume more computing resources during operation, especially when dealing with large-scale problems. This may lead to low efficiency in resource-constrained environments, affecting the practicality and scalability of the model. The current dataset storage solution may not be able to seamlessly expand storage capacity when facing continuous growth in data volume. In the future, further research will be conducted on how to optimize the algorithm structure and computation process while ensuring stable output results, reducing the consumption of computing resources, and improving the performance of the model on large-scale problems. Future research will adopt more efficient distributed storage technology to solve the problem of storage capacity expansion. More diversity protection mechanisms will also be introduced, such as dynamic adjustment of crowding distance, to ensure a more uniform distribution of solutions on the Pareto front. In the face of HR allocation in hospitals, it is necessary to simultaneously optimize the allocation of medical staff, equipment, and beds to improve the efficiency and quality of medical services. For small and medium-sized enterprises, optimization of employee recruitment, training, and promotion strategies should be considered to improve employee satisfaction and retention rates.

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