Digital Marketing Strategies Leveraging Data Fusion and Communication Technology for Effective Human Resource Management and Organizational Configuration

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Abstract. In the new normal economic development environment, strengthening human resource management to obtain core competitive advantages is of key significance for enterprises to cope with market competition and obtain economic benefits. Effective project management is an important way to improve the competitiveness of enterprises, and its core content is project planning, scheduling, and control. Project scheduling is to study and solve how to arrange resources according to time according to various tasks of the project process, so that the predetermined optimization goal can be realized. We propose a memetic algorithm for the classical resource-constrained project scheduling problem. Memetic uses the task linked list as the individual code, the single-point crossover operator as the recombination operator and applies different combinations of five local search processes to improve the offspring individuals. Many cases from three groups of case sets J30, J60 and J120 in RCPSP's standard question library PSPLIB are used to test MA, and the results show that MA has strong competitiveness.

Keywords: project planning;human resource management;Digital Marketing Strategies;project scheduling,

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1 INTRODUCTION

With the changes of the globalized economic development situation, enterprises are facing more and more complex external environment. At this time, strengthening human resource management will help enterprises to improve their risk resistance ability, reduce brain drain, and ensure operational efficiency [16]. Under the new situation, the human resource management of enterprises is more systematic and comprehensive, and it is necessary to adjust the strategic plan in a timely manner in combination with changes in the external environment and internal business conditions, to play a more efficient human resource management function [7]. At the same time, human resource management in the new era places more emphasis on the participation of all employees and the construction of the whole process. The initiative and autonomy of human resource management in various departments should be improved to better stimulate the vitality and creativity of talents and enhance the contribution of human capital to promoting economic benefits. important role. Under the complex and changeable economic situation, enterprises should update human resource management concepts, promote organizational reform, and improve organizational training and performance appraisal systems [21]. At present, the lack of scientific in the management concept, system construction, performance appraisal, and information construction of enterprises makes human resource management activities unable to effectively help enterprises to enhance their core competitive advantages, and seriously affects the stability of their internal operations [2]. Therefore, enterprises should comprehensively analyze the current problems in human resource management, and then build an efficient, dynamic, and flexible human resource management system, and formulate relevant human resource management risk response mechanisms to create an organizational culture that is conducive to ensuring personnel stability. Institutional system to ensure the economic performance of enterprises.

The name Project Management first appeared in the Manhattan Project in the United States. In the early 1960s, famous mathematicians in my country introduced the idea of project management into China, which had a positive impact on the management of related fields in my country. Project management includes project time management, cost management and quality management. Project scheduling is closely related to project time and cost and is one of the core contents of project management [24]. Early project management did not consider resource constraints, but in recent decades, people have increasingly realized that the project scheduling plan prepared using the classical project scheduling methods CPM and PERT often cannot be implemented smoothly under the condition of limited resources. The research on RCPSP can be summarized into two aspects: one is to establish RCPSP models that meet different requirements, and the other is to solve RCPSP algorithms. RCPSP is mostly NP. Hard problems are more difficult to solve. This paper proposes a Memetic algorithm (MA) for RCPSP. MA uses the task linked list as the individual code, the single-point crossover operator as the recombination operator and uses different combinations of five local search processes to improve the offspring individuals [6]. Many cases from the three groups of case sets J30, J60 and J120 in the RCPSP standard problem library PSPLIB are used to test MA, and the results show that MA has strong competitiveness. In the whole process, relying on effective data fusion analysis and the communication of individual codes in the task chain, our method provides effective guidance information for subsequent human resource allocation.

2 RELATED WORK

2.1 Problems Existing in Human Resource Management

First, the human resource management system of the enterprise is not perfect, the connection and cooperation of each module are unreasonable, and there is a lack of integrity and systematization [8]. When enterprises recruit talents, they ignore the combination with the follow-up talent training mechanism and talent allocation mechanism, which leads to the mismatch between talents and job requirements, and it is difficult to attract talents through training and promotion channels [3]. At the same time, the formulation of the compensation incentive system of the enterprise is not scientific and reasonable enough, it is difficult to fully mobilize the enthusiasm and subjective initiative of talent work, and it fails to cultivate the sense of belonging of talents, which makes it difficult for human resource management to improve economic benefits [25]. In addition, the company ignores the follow-up performance feedback when carrying out human resource management activities, so that the work problems and business risks generated by personnel at all levels cannot be solved and fed back in time; secondly, it is difficult for the company to formulate human resource strategies to meet development needs. , the investment in human capital is insufficient, and it is impossible to create a talent management system that can attract employees, thereby affecting the acquisition of corporate economic benefits [22]. Some enterprises lack scientific human resource management concepts, pay too much attention to short-term human cost control, while ignoring long-term human capital investment returns, and pay insufficient attention to talent training and salary incentives, which is prone to brain drain, which in turn causes management problems. confusion, affecting the acquisition of the ultimate economic benefits [9]. And some enterprises only focus on short-term labor cost control and lack a correct understanding of how to accumulate human resources to obtain higher levels of economic performance; finally, enterprises lack a scientific talent allocation mechanism, resulting in an unreasonable human capital structure and affecting various business management activities. successful implementation [1]. Talent allocation is related to the combination of people and positions, the cultivation of subsequent talents, and how to retain the talents of the enterprise. However, the lack of scientific talent development planning in the enterprise makes the enthusiasm of some employees not high, thus restricting the innovation and profit growth of the enterprise.Lastly, digital marketing can enable effective talent development planning and performance feedback mechanisms. Learning management systems and online training programs can be implemented to provide continuous learning and skill development opportunities for employees. Moreover, digital tools can facilitate regular performance evaluations, feedback loops, and goal tracking, enabling timely recognition, support, and corrective actions.

2.2 The Role of Human Resource Management

By improving and innovating human resource management models, enterprises can help them achieve their strategic goals, and can help them find problems such as labor costs, human resource allocation, and brain drain in a timely manner, thereby improving the overall organizational management efficiency of the enterprise. Enterprises build a complete human resource management system, which is helpful to comprehensively control the use of human resources in various departments and improve the standardization of human resource allocation [19]. At the same time, the enterprise builds a human resource management system involving all employees, which can timely discover and feedback human resource problems and risks to various departments, to help each department take effective measures to improve the performance appraisal process, personnel recruitment process, organization training process, etc. Through the formulation of human resources strategy, the enterprise can ensure the future talent selection, talent allocation and talent cultivation, control the risk of future personnel management in advance, reduce the phenomenon of unreasonable personnel allocation to unreasonable positions, and effectively control the enterprise Unnecessary waste of human resources [13]. Specifically, only by setting up a scientific human development strategy can an enterprise improve personnel satisfaction, protect human capital, reduce the negative impact of personnel turnover on the economic benefits of the enterprise, help employees find performance gaps, and promote employees to improve their work efficiency. Reduce work errors [17]. Moreover, when the enterprise formulates reasonable and fair compensation, it can enhance the loyalty of employees, reduce the turnover intention of employees, and promote employees to obtain high performance by improving their own ability level [4]. In addition, under the drastic changes in the external policy environment and market environment, enterprises should formulate scientific employee training plans to improve employees’ understanding of external policies and market conditions, update their ideas and knowledge and skills in a timely manner, and keep up with the development of the times [11]. Talent is the premise of enterprise development, but at the same time, it also generates a lot of labor costs. Only by improving the efficiency of human recruitment, ensuring the performance of human benefits, improving the efficiency of human resource allocation, and meeting the needs of talents in various business management activities, can enterprises pass the human capital. Continue to leverage the economic benefits of more enterprises [20].

2.3 Resource Constrained Project Scheduling Problem

A general RCPSP can be described: a project contains a task, task l is the only task that starts the earliest, and task is the only task that finishes the latest, all of which are virtual tasks (no resource consumption and execution time is 0), represent the beginning and end of the entire project, respectively [10]. The task must choose one of M execution modes for execution (each execution mode corresponds to certain resource requirements and execution time), and the execution mode cannot be interrupted or changed during the execution process. Executing task J in the MTh (1≤m≤Mj) mode requires the kth (seven = 1...., K) type of updateable resources to be rPjr, k, which requires the kth (row = 1...., IV))is an amount of non-updatable resources, and the execution time is time [15]. Virtual task I and, have only one execution mode. If the project starts from phase 0, the upper limit of the project duration is D [12]. During the entire project duration, the available amount of the kth renewable resource in each stage is constant RPk (7=1…., K), and the total amount of the nth non-renewable resource is such as (gate=1…., IV). In addition to resource constraints, due to technical or project organization reasons, there are also time constraints between tasks, and this time constraint relationship is related to the execution mode selected by related tasks [5]. When task i chooses the mjth mode to execute, and task/selects the first mode to execute, the start time S of task i is related to the task, and the start time S needs to satisfy the constraint of formula (1),

$$SS_{m_i m_j}^{\min} \le ST_j - ST_i \le SS_{m_i m_j}^{\max} \tag{1}$$

The SF, FS, and FF-type time constraints between tasks can also be described by Equation (1). Solving RCPSP is to determine the execution mode and start execution time of each task under the condition of ensuring resource constraints and time constraints between tasks, so that one or more project indicators are optimal.

3 METHODOLOGY

3.1 Memetic Algorithm

Memetic algorithm (Memetic Algorithm, referred to as MA) is a swarm intelligence optimization algorithm based on human cultural evolution strategy. The term Meme was first proposed by a British scholar in 1976. In his paper "The Selfish Gene", Meme is used to represent the information unit transmitted by people during communication, which is translated as "cultural gene" or "cultural genetic factor". Meme will change due to personal thoughts and understanding in the process of dissemination, so the information passed from the parent to the child can be changed, which is manifested in the process of local search in the algorithm. In 1992, the Memetic algorithm was formally proposed and applied to the optimal solution of the traveling salesman problem. In 1994, he introduced the Memetic algorithm in detail in the paper (Formal memetic algorithms), discussed the optimization mechanism of the algorithm, and focused on the local search strategy of the algorithm. Since then, the Memetic algorithm has attracted the attention of many scholars, and the research content and application fields have also been continuously expanded and deepened. Like the genetic algorithm that simulates the biological evolution process, MA is an algorithm that simulates the cultural evolution process. The mechanism of combining global search and local search of MA makes its search efficiency higher than that of traditional GA in some problems and is widely used in solving complex problems. In essence, MA proposes a framework and a concept. Under this framework, different local search methods are used to form different algorithms. For example, the global search strategy can use genetic algorithm, evolution strategy, etc. The strategy can use simulated annealing, tabu search, greedy algorithm, guided local search, etc. The execution process of MA is to initialize the population first, generate a set of chromosomes with reasonable spatial distribution (random solution), and then obtain the optimal solution (near-optimal solution) through local search. In each iteration, chromosomes are updated through crossover, mutation, and local search. The algorithm flow is shown in Figure 1.

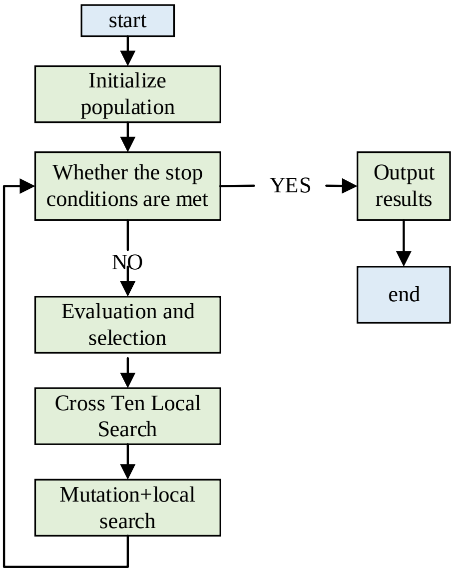

Figure 1: Memetic Algorithm Flow.

It can be seen from the flow of the algorithm that IvlA fully absorbs the advantages of GA and LS. MA not only has a strong global optimization ability, but also performs Local Search after each crossover and mutation and eliminates bad individuals as soon as possible. By optimizing the population distribution, it reduces the number of iterations, improves the solution efficiency, and ensures the quality of the output solution. MA combines the genetic algorithm with the local search process. From the perspective of genetic algorithm, MA is a standard genetic algorithm that runs on the local optimal solution. Compared with the standard genetic algorithm, its efficiency is mainly reflected in the reduction of the search space. From the point of view of local search algorithm, MA is a local search algorithm starting from multiple points. Compared with the local search algorithm starting from multiple points, the efficiency of MA can be explained as starting from multiple better solutions for local search., the optimal solution (near-optimal solution) can usually be reached after less iterations.

3.2 Solving the MA of RCPSP

In this paper, MA uses the task linked list satisfying the priority relationship as the individual encoding and uses the serial scheduling scheme to decode. When using the meta-heuristic algorithm to solve the RCPSP, the operator usually acts on the encoding of the individual rather than the problem solution itself, and then obtains a task scheduling scheme that meets the requirements by invoking the appropriate encoding and decoding processes. For decades, many scholars have proposed many meta-heuristic algorithms for RCPSP, and these algorithms are worthy of reference in the process of designing RCPSP solving algorithms. The encoding methods of the meta-heuristic algorithm for solving RCPSP are classified into five kinds: task linked list encoding, task priority value linked list encoding, scheduling rule linked list encoding, shift vector linked list encoding and scheduling scheme linked list encoding. According to the research conclusion, the meta-heuristic algorithm using task linked list encoding and serial scheduling scheme (SSS) decoding is better than other encoding methods. Therefore, the MA proposed in this paper is encoded using a linked list of tasks and decoded using the SSS process.

3.3 Sorting Of Non-Dominated Sets

In 1994, a non-dominated sorting method based on sorting selection and niche technology was proposed, and a non-dominated genetic algorithm (NSGA) for solving multi-objective optimization problems was proposed combined with genetic algorithm. After that, in 2002, the calculation of the non-dominated ranking level in NSGA and the fitness sharing strategy that needs to set the sharing radius were improved, and NSGA-II was proposed. The calculation time complexity of the non-dominated ranking level in NSGA-II is lower., and the calculation of crowding degree distance does not need to set parameters manually, this paper adopts the method of sorting non-dominated sets in NSGA-II to calculate the level and crowding degree distance of everyone. The selection of individuals in MOCS is based on the comparison between individual individuals, that is, for each individual j nest in the population nest, an individual ' i nest is randomly selected in the newly generated population ' nest, if ' i nest dominates j nest, then Replace j nest with ' i nest. In IMOCS, combine nest and ' nest to form a population tempnest containing 2n individuals, sort tempnest as a non-dominated set, and add two attributes rank i and distance i to each individual i in tempest. Select n individuals from tempnest, first select individuals with lower levels, and if the levels are the same, select individuals with greater crowding.

4 EXPERIMENTS

4.1 Evaluation Indicators

Two performance evaluation indicators are used in the experiment: the generalized distance GD (Generational Distance) and the diversity of the Pareto frontier (* P). GD is used to measure the closeness of the desired *P to the real frontier P. The smaller the GD, the closer the desired *P is to P. The definition of GD is as follows:

$$GD = \frac{1}{|P^*|}\left(\sum_{i=1}^{|P^*|} d_i^p\right)^{1/p} \tag{2}$$

Among them, id is the Euclidean distance between the ith individual and the corresponding real Pareto frontier, p is the number of objectives in the optimization problem, and for the optimization problem of two objectives, p = 2. Population diversity is defined as formula (3):

$$\Delta = \frac{1}{\sum_{m=1}^{p} d_m^e + |P^*|\bar{d}}\left(\sum_{m=1}^{p} d_m^e + \sum_{i=1}^{|P^*|-1}\left|d_i - \bar{d}\right|\right) \tag{3}$$

where it is the Euclidean distance between two adjacent points in *P, d is the average of all ids, and em d is the sum of the boundary solution of *P found on the MTh target and the extreme solution of the true Pareto frontier P. distance between. Considering both the breadth and uniformity of the required *P distribution, em d is used to measure the breadth of the *P distribution, and || id d is used to measure the uniformity of the *P distribution. For a set of ideal Pareto frontiers (uniform distribution id d, em d =0), =0, therefore, the smaller is, the better the diversity of the Pareto frontier is. Dimension d = 30 in test cases ZDT1, ZDT2, ZDT3, d = 10 in ZDT4, and d = 5 in LZ. In the IMOCS algorithm, it is found that the probability 0.5 a p is the same as that of MOCS. The initial value of dynamic adaptive change 0 of SCH, ZDT1, ZDT2, and ZDT3 is 0.1, the change rate K=1.07, the threshold value T=0.3, and 0 is limited to [0.01,2]; ZDT4, the initial value of the dynamic adaptive change 0 of LZ is 0.5, the change rate K=1.07, the threshold value T=0.15, and 0 is limited to [0.1,5]. The settings of the above parameters, the limited range of 0, the rate of change K, and the threshold T are obtained from multiple experiments.

4.2 Non-Dominated Set Sorting Performance Analysis

In this paper, the IMOCS algorithm is programmed and implemented in the computing environment of Pentium(R) Dual-Core T4300 @2.10GHz CPU, 2GB RAM, Windows 7, and MATLAB 2010b. In the experiment, the randomness of the data will have a certain impact on the test results. To reduce this impact and reflect the performance of the algorithm more accurately, each algorithm is run independently for 10 times in the test, and then the average and variance of the GD sum are calculated. The effect of step size control on IMOCS performance. To verify the influence of the step size control variable 0 on the performance of IMOCS, this paper conducts comparative tests on the performance of IMOCS when 0 is fixed (0 = 0.01) and 0 is dynamically adaptively changed. Setting n=200, Mixite=100, Table 1 gives the mean GD and variance 2 of GD between *P and P for 6 test instances, and Table 2 gives the mean and variance 2 of *P. It can be seen from Table 1 that the dynamic adaptive change of 0 makes the IMOCS have better performance than the fixed value, and the GD of the Pareto frontier of all test cases is reduced compared with the fixed value of 0, that is, when the dynamic value of 0 in the IMOCS is 0 When adaptively changing, the desired Pareto front is closer to the real Pareto front. And it can be seen from Table 2 that when 0 in IMOCS changes dynamically and adaptively, the diversity of the Pareto fronts it seeks is also better.

algorithm	*SCH*		*ZDT1*		*ZDT2*		*ZDT3*		*ZDT4*		*LZ*	
	$\overline{GD}$	δ^2	$\overline{GD}$	δ^2	$\overline{GD}$	δ^2	$\overline{GD}$	δ^2	$\overline{GD}$	δ^2	$\overline{GD}$	δ^2
IMOCS/fixe $d\alpha_0$	*5.72 E-05*	*8.45 E-11*	*1.83 E-05*	*4.50 E-08*	*1.64 E-05*	*3.97 E-08*	*6.47 E-06*	*1.45 E-08*	*1.37 E-02*	*5.25 E-04*	*3.72 E-04*	*5.08 E-06*
IMOCS/dyna $mic\alpha_0$	*3.79 E-06*	*5.37 E-11*	*8.06 E-07*	*5.66 E-12*	*9.99 E-07*	*8.47 E-12*	*1.04 E-06*	*1.67 E-13*	*1.23 E-06*	*1.26 E-12*	*1.68 E-04*	*2.44 E-07*

Table 1: Mean value and variance of GD obtained when step size control variable is dynamically adaptive and fixed.

Figure 2 presents the Pareto frontier for each test case. For ZDT4, the IMOCS under the dynamic adaptive change is 4 orders of magnitude smaller than that required by the fixed IMOCS, which is a great improvement, because the fixed IMOCS fails to search the global Pareto front in 10 independent runs, and the IMOCS under dynamic adaptive changes all search for the global Pareto frontier, so this is more intuitively reflected in the Pareto frontier diagram of ZDT4.

algorithm	*SCH*	*ZDT1*	*ZDT2*	*ZDT3*	*ZDT4*	*LZ*

	$\overline{\Delta}$	δ^2	$\overline{\Delta}$	δ^2	$\overline{\Delta}$	δ^2	$\overline{\Delta}$	δ^2	$\overline{\Delta}$	δ^2	$\overline{\Delta}$	δ^2
IMOCS/fixe $d\alpha_0$	5.15 E-02	1.75 E-05	5.87 E-02	1.12 E-04	5.66 E-02	9.85 E-05	7.06 E-02	1.18 E-04	7.66 E-02	6.28 E-04	1.41 E-00E	1.69 E-03
IMOCS/dyna $mic\alpha_0$	4.66 E-02	2.14 E-05	5.14 E-02	7.73 E-04	5.15 E-02	2.38 E-03	6.88 E-02	1.74 E-04	6.03 E-02	3.18 E-04	9.62 E-02	2.26 E-02

Table 2: The mean value and variance of diversity obtained when the step size control variable is dynamically adaptive and fixed.

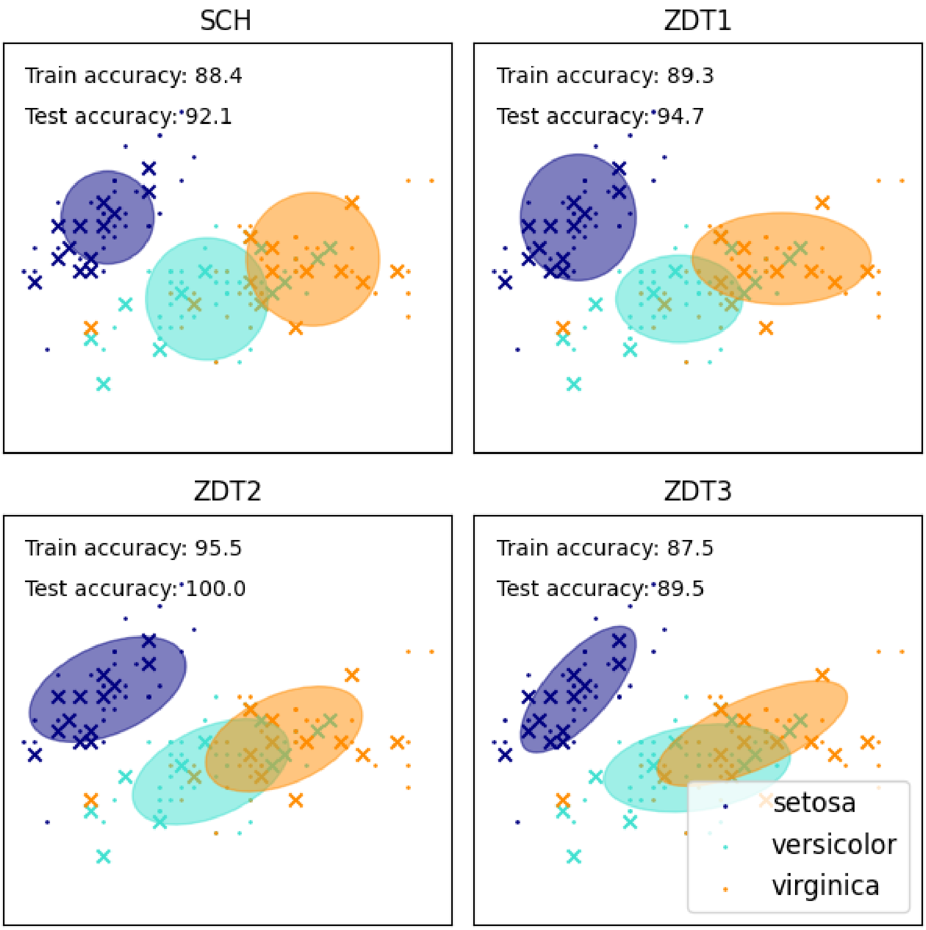

Figure 2: Pareto Frontier of Test Cases.

Figure 3 presents the GD convergence curves for the 6 test cases. For the SCH with only one-dimensional variables, the two types of IMOCS under 0 converge very quickly; for ZDT1, ZDT2, ZDT3, the IMOCS under the dynamic adaptive change 0 is significantly faster than when 0 is fixed; for ZDT4, at 30 times Before the iteration, the GD curve obtained by IMOCS under dynamic adaptive change 0 is above the GD curve obtained by IMOCS under fixed 0. This is mainly because the IMOCS under dynamic adaptive change 0 is in the exploration period, and the change range of 0 is large. After 30 iterations, the GD curve obtained by IMOCS under the dynamic adaptive change of 0 is below the GD curve obtained by IMOCS under fixed 0, and the final magnitude of GD is e-5, which is reflected in Fig. 2(e) as The IMOCS under dynamic adaptive change 0 reaches the global Pareto front, while the IMOCS under fixed 0 falls into the local Pareto front, and its final GD order of magnitude is e-2; it can be seen from the convergence curve of LZ that under fixed 0 There are several obvious fluctuations in the GD value of the IMOCS in the search, while the IMOCS under the dynamic adaptive change 0 is relatively stable. The dynamic adaptive change of 0 can make the IMOCS converge quickly and stably.

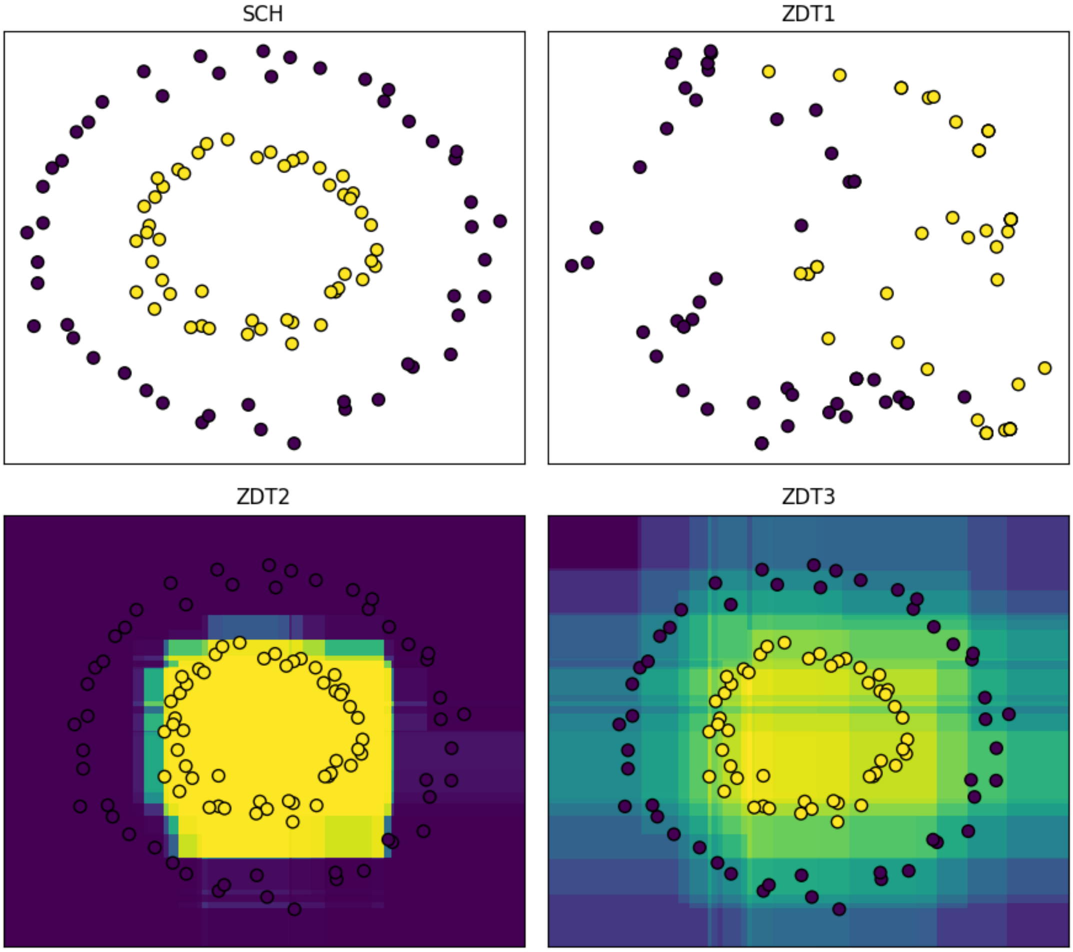

Figure 3: GD Convergence Curve of Test Cases.

Figure 4 shows the change curve of 0 of dynamic adaptive change during 1000 iterations, and its test example is ZDT4. It can be seen from Figure 4 that before 40 iterations, the value of 0 fluctuates greatly, which is an adaptive adjustment process of 0. The algorithm is in the exploration period, and the value of GD decreases rapidly during this period. The convergence curve of GD is shown in

Figure 3(e); from 40 iterations to 70 iterations, the value of 0 is stable at around 1.3, and the algorithm is in the convergence period, during which the value of GD slowly decreases to the order of magnitude e -4 Nearby, it indicates that the search reaches the global Pareto front, which is shown in Figure 2(e) as the IMOCS under dynamic adaptive change 0 reaches the global Pareto front, while the IMOCS under fixed 0 falls into the local Pareto front; after 70 iterations, The value of 0 gradually decreases, and becomes the set minimum value of 0.1 after 120 times. The algorithm has entered a stagnation period. After that, the value of GD stabilizes around the order of magnitude e -5, and there is no obvious change.

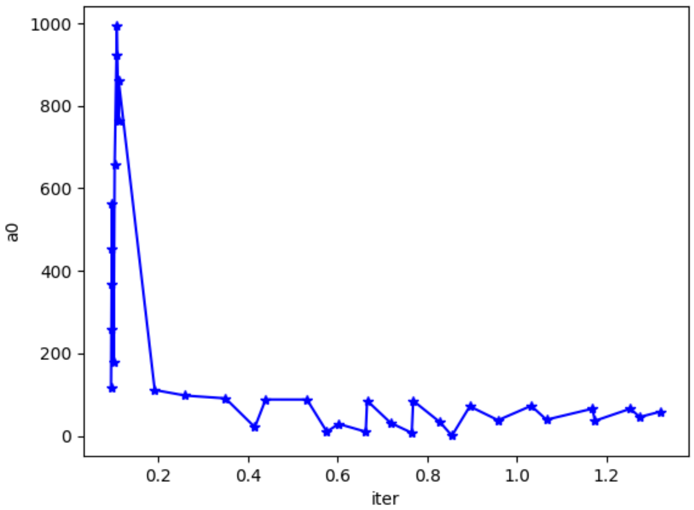

Figure 4: Variation Curve of an in ZDT4.

Performance comparison analysis of IMOCS and MOCS. To verify the effectiveness of the IMOCS algorithm, this paper compares its performance with MOCS. The GD values of five test instances of MOCS at n=50, Mixite=500 is given. In this paper, the GD values of IMOCS under the same conditions are calculated, and the experimental results of the two algorithms are listed in Table 3. It can be seen from the table that the GD values required by IMOCS are all smaller than MOCS, indicating that the performance of IMOCS is better than that of MOCS.

algorithm	*SCH*	*ZDT1*	*ZDT2*	*ZDT3*	*LZ*
MOCS	*1.25E-08*	*1.17E-08*	*2.23E-06*	*2.88E-06*	*4.16E-06*
IMOCS/dynamic α_0	*7.69E-08*	*1.09E-08*	*1.47E-08*	*3.42E-08*	*3.16E-06*

Table 3: GD Values Calculated by IMOCS and MOCS.

The test results of 4 test instances of NSPSO at n=200 and Mixite=100 are given, and the test results of IMOCS under the same conditions are given in this paper. Table 4 shows the mean and variance 2 of GD between *P and P for the 4 test instances, and Table 5 shows the mean and variance 2 of *P. It can be seen from Table 4 that for the ZDT series, the GD obtained by IMOCS is 1-2 orders of magnitude smaller than that of NSPSO, which means that the Pareto front obtained by

IMOCS is closer to the real Pareto front than that obtained by NSPSO, and its solution deviation is smaller. IMOCS solution is more stable. It can be seen from Table 5 that the requirements of IMOCS are all smaller than those of NSPSO, which indicates that the diversity of Pareto fronts required by IMOCS is better, and its deviation is smaller, which further shows the stability of IMOCS.

algorithm	*ZDT1*		*ZDT2*		*ZDT3*		*ZDT4*	
	$\overline{GD}$	δ^2	$\overline{GD}$	δ^2	$\overline{GD}$	δ^2	$\overline{GD}$	δ^2
NSPSO	*7.78 E-05*	*8.14 E-06*	*8.06 E-05*	*3.06 E-06*	*3.41 E-04*	*2.55 E-05*	*7.83 E-05*	*6.92 E-06*
IMOCS/dynamic α_0	*8.06 E-07*	*5.66 E-12*	*9.99 E-07*	*8.47 E-12*	*1.04 E-06*	*1.67 E-13*	*1.23 E-06*	*1.26 E-12*

Table 4: GD mean, and variance calculated by IMOCS and NSPSO.

algorithm	*ZDT1*		*ZDT2*		*ZDT3*		*ZDT4*	
	$\overline{\Delta}$	δ^2	$\overline{\Delta}$	δ^2	$\overline{\Delta}$	δ^2	$\overline{\Delta}$	δ^2
NSPSO	*7.68 E-02*	*3.01 E-03*	*7.59 E-02*	*2.78 E-03*	*9.15 E-02*	*3.94 E-03*	*7.69 E-02*	*3.58 E-03*
IMOCS/dynamic α_0	*5.14 E-02*	*7.73 E-04*	*5.15 E-02*	*2.38 E-03*	*6.88 E-02*	*1.74 E-04*	*6.03 E-02*	*3.18 E-04*

Table 5: Mean and Variance of Diversity Calculated by IMOCS and NSPSO.

Its performance was compared with that of NSGA-II. Deb improved NSGA in 2002 and proposed NSGA-II but did not give an experimental analysis. The GD values of five test instances of NSGA-II at n=50 and Mixite=500 is given. In this paper, the GD values of IMOCS under the same conditions are calculated, and the experimental results of the two algorithms are listed in Table 6. It can be seen from Table 6 that the GD values required by IMOCS are all smaller than NSGA-II, indicating that the performance of IMOCS is better than that of NSGA-II.

algorithm	*SCH*	*ZDT1*	*ZDT2*	*ZDT3*	*LZ*
NSGA-II	*5.73E-04*	*3.33E-03*	*7.24E-03*	*1.14E-02*	*4.19E-03*
IMOCS/dynamic α_0	*7.69E-08*	*1.09E-08*	*1.47E-08*	*3.43E-08*	*3.16E-06*

Table 6: GD Values Calculated by IMOCS and NSGA.

4.3 MA Performance Analysis

To determine the algorithm parameter values of MA, the author firstly conducted some preliminary experiments. In the preliminary experiment, the MA solves the first case under each seed in a set of J120 cases (ie cases J1201 1.SM, J1202-1.SM, J12060_1.SM). Given that LSHY'BRID embeds other 4 local search procedures, to reduce the computational complexity, only the LSHYBRID local search procedure is applied in the preliminary experiments. First, to test the crossover probability P. Influence on MA performance, take pop Size=80, Gen=30, mixite=20, P. = {0.75, O. 80, O. 85, 0.90), run MA to solve each problem case 4 times, and set different hoist values each time. The calculation results are shown in Table 7. The column label "Sum" in Table 7 represents the total duration of the 60 cases: the column label "Best" indicates the number of cases with the same duration as the current best result given by MA (data from PSPLIB, August 31, 2013); The calculation results in Table 7 show that: when pc=O. Algorithm performance is best when 80. Next, set P. =O. 80, test the effect of pop Size, Gen, and master on MA performance. The calculation results are shown in Table 8.

P_C	Sum	Best	Avg. Dev (%)	Avg. CPU	Max. CPU
0.75	7391	27	29.94	55.26	104.38
0.81	7384	28	29.84	55.48	102.79
0.86	7388	29	29.92	58.35	120.05
0.91	7393	25	30.01	59.76	114.55

Table 7: Impact of pe Value on MA Execution Results (pop Size=80, Gen=30, mart=20).

pop size	Gen	Max Iter	Sum	Best	Avg. Dev (%)	Avg. CPU	Max. CPU
60	31	21	7388	28	29.89	54.21	100.65
60	41	16	7392	28	29.94	56.32	108.49
60	41	21	7388	28	29.87	68.24	137.28
60	51	16	7393	26	29.97	66.79	120.03
60	51	21	7388	27	29.92	80.51	147.53
80	31	16	7384	27	29.84	55.49	102.79
80	31	21	7384	28	29.84	55.48	102.79
80	41	16	7378	27	29.77	74.96	137.48
80	41	21	7379	28	29.72	91.62	173.35
80	51	16	7387	27	29.85	88.95	168.32
80	51	21	7369	28	29.59	109.89	213.26
100	31	16	7385	29	29.82	77.49	140.18
100	31	21	7382	29	29.77	94.15	183.19
100	41	11	7394	27	29.99	76.75	148.84
100	41	16	7376	28	29.69	99.03	194.08
100	41	21	7374	29	29.65	115.49	219.71
100	51	11	7373	27	29.67	91.28	165.65
100	51	16	7372	29	29.63	117.02	214.82
100	51	21	7372	32	29.61	137.11	244.65

Table 8: Impact of the parameters pop size, Gen and mall on MA execution results (p=0.80).

When maxlter=5, none of the parameter combinations satisfy the "Avg.Dev." value of less than 30.00%. In the parameter combinations that satisfy the "Avg.Dev." value of less than 30.00%, the influence of different combinations on the execution result of MA is not obvious. The random calculation result shows that the value of "Avg.Dev." is the smallest when popSée=80, Gen=50, and maxlter=20. Therefore, in the subsequent formal testing process, the algorithm parameters are set as follows: popSme=80, Gen=50, maxBer=20, P. = 0.80, preGen=10 and elitism=5. However, the computation time of the MA using LSHYBRID is significantly increased compared to the MA using the other three local search procedures. In terms of comprehensive solution quality and time efficiency, the MA comprehensive performance using the LSENINSERT local search process is the best. See Table 9.

In the past few decades, there have been many heuristic algorithms for solving RCPSP. These algorithms are often coded in different computer languages and run-on different machine platforms, so it is difficult to compare their performance.

Problem set	local search	J30	J60	J120
Sum	LSSWAP	28344	38559	75444
	LSINSERT	28318	38395	74472
	LSENINSERT	28317	38378	74405
	LSHYBRID	28317	38359	74182
Best	LSSWAP	461	379	227
	LSINSERT	479	416	265
	LSENINSERT	481	429	275
	LSHYBRID	481	437	293
Avg. Dev (%)	LSSWAP	0.09	11.13	32.93
	LSINSERT	0.02	10.64	31.23
	LSENINSERT	0.01	10.59	31.12
	LSHYBRID	0.01	10.54	30.72
Avg. CPU	LSSWAP	0.08	1.63	22.22
	LSINSERT	0.05	2.66	21.95
	LSENINSERT	0.04	3.14	27.64
	LSHYBRID	0.06	10.95	107.13
Max. CPU	LSSWAP	1.37	6.87	41.23
	LSINSERT	3.74	12.24	42.04
	LSENINSERT	4.42	14.58	53.68
	LSHYBRID	4.06	50.12	211.27

Table 9: Main Calculation Results of MA.

To have a fair comparison criterion, a method is proposed to ensure fair comparison of all algorithms on the PSPLIB case set, that is, using generating 1000, 5000 and 50000 solutions as the termination condition of the algorithm. Tables 10 to 12 show the comparison between the calculation results of MA using the local search process LSENINSERT and the calculation results of six excellent algorithms for the case sets J30, J60 and J20. The 6 excellent algorithms selected include the 4 algorithms presented in the review.

algorithm	Maximum number of scheduling plans		
	1000	5000	50000
Ranjbar, etc.	0.11	0.04	0.00
Kochetov and Stolyar	0.11	0.05	0.00
MA+ LSENINSERT	0.12	0.05	0.00
Debels et al	0.28	0.12	0.02
Debels and Vanhoucke	0.13	0.05	0.03
Valls et al	0.28	0.07	0.03
Alcaraz et al	0.26	0.07	0.04

Table 10: Average deviation between solution result and optimal solution (J30).

It can be seen from Table 10 to Table 12 that the solution time is appropriately increased under acceptable conditions. For the J30, J60 and J120 case sets, the calculation results of MA are better than those of the compared algorithms.

algorithm	*Maximum number of scheduling plans*		
	1000	*5000*	*50000*
Ranjbar, etc.	*11.58*	*11.08*	*10.65*
Kochetov and Stolyar	*11.72*	*11.18*	*10.75*
MA+ LSENINSERT	*11.72*	*11.29*	*10.64*
Debels et al	*11.74*	*11.11*	*10.72*
Debels and Vanhoucke	*11.32*	*10.96*	*10.69*
Valls et al	*11.57*	*11.11*	*10.74*
Alcaraz et al	*11.89*	*11.19*	*10.85*

Table 11: Average Deviation between Solution Results and Critical Path Length (J60).

algorithm	*Maximum number of scheduling plans*		
	1000	*5000*	*50000*
Ranjbar, etc.	*35.09*	*34.12*	*31.46*
Kochetov and Stolyar	*34.75*	*33.37*	*32.07*
MA+ LSENINSERT	*35.19*	*34.12*	*31.47*
Debels et al	*35.23*	*33.11*	*31.58*
Debels and Vanhoucke	*11.32*	*10.96*	*10.69*
Valls et al	*11.57*	*11.11*	*10.74*
Alcaraz et al	*11.89*	*11.19*	*10.85*

Table 12: Average Deviation between Solution Results and Critical Path Length (J20).

5 CONCLUSION

In today's more complex economic development situation, enterprises should correctly analyze and understand the system problems, strategy formulation stability, personnel allocation problems, and personnel mechanism problems existing in human resource management activities. This paper uses MA to encode individuals with task linked list, uses single-point crossover operator as recombination operator, and applies five local search processes to improve offspring individuals. The algorithm performance is tested using many cases from the case sets J30, J60 and J120 in PSPLIB. In addition, we use the model and method of multi-objective optimization problem, and the selected test cases are the optimization functions of two objectives. At the same time, the non-dominated set sorting algorithm in IMOCS is not limited by the number of objectives and decision variables. It is feasible to apply the IMOCS algorithm to the multi-objective optimal management in the actual human resource project.

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