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Application of Hybrid Particle Swarm Multi-objective Optimization Algorithm in Engineering Project Management

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Abstract: Particle Swarm Optimization (PSO) algorithm has the characteristics of simple principle, few parameters, high parallelism efficiency and easy implementation, it is widely used in various fields, and the PSO algorithm is an algorithm based on swarm intelligence search, which can be parallelized. Particle swarm optimization algorithm is an evolutionary computing technology based on swarm intelligence method, and it is a new branch in the field of evolutionary computing. Exploration of multiple feasible solutions that meet the conditions is more suitable for solving multi-objective optimization problems. Because the algorithm is easy to combine with other algorithms, it has broad application prospects in many complex combinatorial optimization fields. The purpose of this paper is to use the organic combination of the improved hybrid particle swarm multi-objective optimization algorithm and engineering project management to effectively solve the optimization problem of the entire project supply chain management, discuss and predict the possible problems and countermeasures in the theoretical research and application fields, and then propose improvement plans. Hybrid particle swarm multi-objective optimization algorithm. At the same time, an improved hybrid particle swarm multi-objective optimization algorithm is used to make material selection decisions in project management to achieve the goal of maximizing project benefits. The hybrid particle swarm multi-objective optimization algorithm has outstanding advantages in solving many difficult and complex combinatorial optimization problems. This paper first expounds the theory and important parameters of the hybrid particle swarm multi-objective optimization algorithm, and then analyzes its improvement and application in parameter optimization and intelligent fusion. Finally, it summarizes its application in engineering applications, such as: job scheduling problem, vehicle routing problem, image processing, power system optimization and other aspects of the application progress. Therefore, it can be concluded that the application of the improved optimization algorithm can avoid unfavorable factors in production in project management, seek to maximize benefits, and make production more convenient and efficient. Therefore, the research on hybrid particle swarm multi-objective optimization algorithm is used in engineering project management. It is of great significance. Intelligent decision system plays an important role in project management.

1. Introduction

As an important research direction of complex systems, optimization has attracted the attention of academia, especially in the field of production scheduling, including continuous systems and discrete systems [1-3]. As pointed out by a professor at Harvard University's American Academy of Engineering, "Any control and decision-making problem can be reduced to an optimization problem in nature" [4-5]. Optimization plays an important role in improving production efficiency and economic benefits. Therefore, optimizing the production process has become one of the main goals that the business community expects to achieve at an early date. We know that the hybrid particle swarm multi-objective optimization algorithm first summarizes the characteristics and behavior of the ant colony by observing the ants in nature, and turns it into a general optimization algorithm, which depends on the algorithm's own search method in terms of actual complexity. Artificial ants are usually used in correlation simulations, so the corresponding system will be called an ant system [6].

Due to the temporary and unique nature of project construction, there are still many problems and processes that need to be optimized in this very traditional industry. Especially in the era of highly developed information and communication technology, the organizational structure of engineering projects is becoming more and more refined. Intangible assets present a greater challenge for the unique complexity of the process and less common specific projects [7-8]. How to use these advanced information and communication technologies to improve the activities of traditional engineering construction, so that they can achieve more effective management, less manpower and material resources to complete the cost of the same page results of East China University of Science and Technology, or further increase the value of project results [9]. Therefore, in the actual project management planning and implementation phases, it is not enough to look for original similar experiences. Especially for the large-scale application of modern technology, it is more important to consider the uniqueness of the project [10].

Currently, researchers' interest in hybrid particle swarm multi-objective optimization algorithms has increased dramatically, and hybrid particle swarm multi-objective optimization algorithms are increasingly successful in solving combinatorial optimization problems. Among them, the most widely used is NP-hard problem, that is, it is difficult to find the optimal solution of the problem in the calculation time of polynomial. In other words, an algorithm is needed to ensure that an optimal solution is applied to a problem of complexity with worst-case exponential time [11]. There are currently two approaches to this problem: exact algorithms and approximate algorithms. Exact algorithm refers to obtaining the optimal solution of the problem through a certain computing time. However, using an exact algorithm to solve NP-hard problems is actually very difficult because the algorithm requires a lot of computational time. In the worst case, an exact algorithm may require exponential running time to find the optimal solution to a problem. However, with the increasing scale of engineering project management, the time of the algorithm is also increasing, which seriously affects the efficiency of many current algorithms in practical problems [12]. An accurate algorithm is no longer suitable as an efficient solution. At present, in order to solve the problem of low execution speed of the exact algorithm, an approximate solution algorithm is proposed, which improves the execution efficiency of the exact algorithm by sacrificing the solution speed and quality of the optimal solution. The innovation of this paper is: using the hybrid particle swarm multi-objective optimization algorithm to study engineering-related management.

2. The Proposed Method

The mobile communication intelligent decision support system is used in project management. At present, a difficult and hot issue in project management, that is, the flexible scheduling method of resources among group projects, is an urgent problem to be solved in related engineering applications [13]. How to reasonably allocate resources and achieve the purpose of maximizing profits is a problem to be solved at present. The current research on this typical NP-hard problem mainly focuses on the research of mathematical models and heuristic models.

2.1. The Basic Principle of Multi-Objective Particle Swarm Optimization Algorithm

The multi-objective particle swarm optimization (MOPSO) algorithm was proposed by Carlos A. PSO algorithm refers to particle swarm algorithm, which has the advantages of fast convergence speed, few parameters, and simple and easy-to-implement algorithm. In recent years, various improvements to the multi-objective particle swarm optimization algorithm have emerged one after another. In real life, there are many optimization problems that are difficult to compute. For multi-objective optimization problems, the increase of decision variables or the increase of the objective dimension of the optimization problem will make the scale of the optimization problem larger and more complex. The evolutionary algorithms used are based on the solutions obtained by the continuous iteration of the population, which will result in high computational overhead. The PSO algorithm itself has the characteristics of parallelization. Combined with the current rapidly developing parallel and distributed hardware computing environment, the parallelized PSO algorithm has been developed rapidly.

$$j = \begin{cases} \arg\max\limits_{l \in N_i^k}\{\tau_{il}(t)\eta_{il}^{\beta}\}, q \le q_0 \\ \arg\max\{p_{il}^{\beta}(t)\}, q > q_0 \end{cases} \tag{1}$$

The swarm intelligence optimization algorithm is mainly a stochastic optimization algorithm that imitates the group behavior of natural creatures such as birds, fish, insects and beasts. We take ants as an example for in-depth analysis. Where is a random variable uniformly distributed in the interval [0, 1]. It is a tuning parameter that can effectively change the search process of ants in the path. Parameter values can significantly affect the time efficiency and algorithm performance of the algorithm. When the parameter is, the selection of the next city node will be based on the location of the ant pheromone and the heuristic information in the path selection process. While it can significantly speed up the algorithm's convergence, it has a large search range. Limit; but when, the ant colony chooses AS's random probability rule to get the location of the next city. It can not only expand the exploration space of ants, but also get more efficient solutions, but it will slow down the convergence speed.

Therefore, combining ACS can not only speed up the execution efficiency of the algorithm, but also obtain a better solution with probability in the process of finding a path with probability. This is a key parameter

In terms of pheromone update, there are two ways to use ACS method: global update of information update and local update of pheromone update. Pheromone refers to the secretion of an individual into the body, and is detected by other individuals of the same species through the olfactory organ, causing the latter to show a certain behavior, emotion, Substances with altered psychological or physiological mechanisms, which have the function of communication. In terms of global pheromone update, AS allows all ants to release pheromones and volatilize all path pheromones on their paths. ACS only allows the best ants to release pheromones so far, and only achieves the volatilization of pheromones on the best path so far. The pheromone concentration on the best path so far is updated as follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}^{bs} \tag{2}$$

The value of is exactly the same as that of MMAS, selecting the best ant to release the pheromone. But it is different from MMAS as far as the expression formula is concerned.

For local pheromone updates, the only update method for ACS is

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \varphi\tau_0 \tag{3}$$

It is a parameter that is the initial value of the pheromone. The effect of this local update is that as the ant travels through each path, the pheromone concentration of the path decreases, causing the latter ants to be less likely to choose a path.

2.2. Improved Hybrid Particle Swarm Multi-Objective Optimization Algorithm

Optimization algorithm based on mobile communication intelligent decision support system. The hybrid particle swarm multi-objective optimization algorithm is based on the principle that ants can always find the shortest path in the process of foraging, and the traveling salesman problem is also the shortest path. Therefore, the hybrid particle swarm multi-objective optimization algorithm has a natural close relationship with the traveling salesman problem, so the cost of using the hybrid particle swarm multi-objective optimization algorithm to solve the traveling salesman problem will be lower.

(1) TSP mathematical model

The traveling salesman problem can be described as: a salesman goes to a city to sell goods, traverses all the cities, and finally returns to the starting point. Set the distance from city to city and the distance between the shortest paths the salesperson should take.

Mathematical model of TSP: It is a weighted weighted graph, a set of vertices, and the distance from a set of vertices to vertices. The mathematical model of TSP is the most basic route problem. This problem is to seek a single traveler starting from the starting point, passing through all the given demand points, and finally the minimum path cost to get back to the origin.

$$\min F = \sum_{i \neq j} d_{ij} * x_{ij}, st. \tag{4}$$

$$x_{ij} = \begin{cases} 1, \text{edge } e_{ij} \text{ is on the optimal path} \\ 0, \text{edge } e_{ij} \text{ is not on the optimal path} \end{cases} \tag{5}$$

$$\sum_{i \neq j} x_{ij} = 1,\ j \in V \tag{6}$$

$$\sum_{i \neq j} x_{ij} = |S|, \text{subgraphs with S as G} \tag{7}$$

Among them, for is the total number of vertices, equation (4) is the objective function, and the constraints of the objective function are equations (5) (6), ensuring that each node has only one entry node and one exit node.

(2) Improvement based on heuristic factors

The basic hybrid particle swarm multi-objective optimization algorithm selects the next node according to the principle of the shortest path of adjacent nodes, that is, the closer the city is to the city, the ants will choose the city with high probability. The positive feedback will further amplify the error value. This will cause the ants to look in the wrong direction, thereby affecting the performance of the entire algorithm. In this case, the last chosen path is not necessarily the best path, so the total length of the final path is not necessarily the smallest. Need to reach point D. As shown in Figure 1, ACD is the shortest path. In addition, the ants choose the path ABD, and the length of the path ABD is 6, which is greater than the length of the path ACD by 4.5.

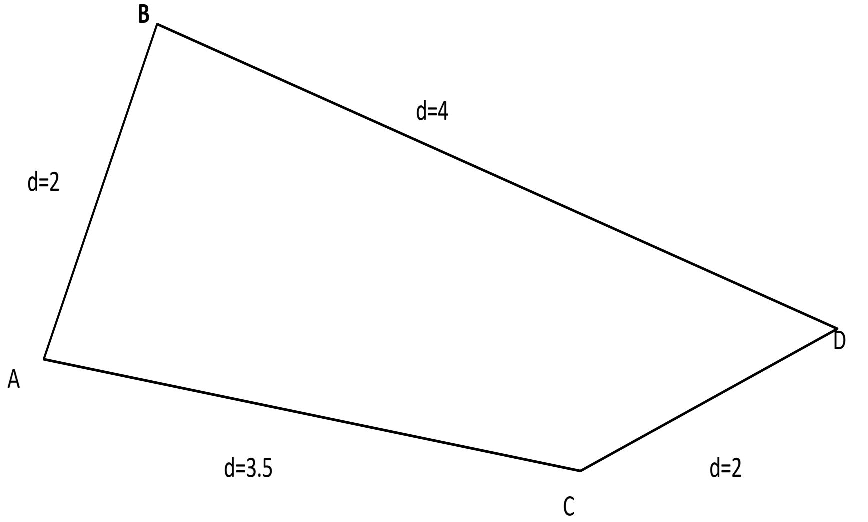

Figure 1: Path selection diagram based on intelligent decision support system

As can be seen from the above example, the hybrid particle swarm multi-objective optimization algorithm selects the next node according to the principle of the shortest path between two adjacent nodes (one step). The result obtained is not necessarily optimal, so consider the path distance between three nodes (two steps) and use this strategy to improve the heuristic. According to the formula, the larger the heuristic factor, the smaller the heuristic factor, and the smaller the transition probability. The improvements are as follows:

$$\eta = \frac{1}{d_{ij} + d_{j.k}} \tag{8}$$

where is the straight-line distance between two points and , and the nodes are selected according to the formula:

$$j = \begin{cases} j, D(i,j) + D(j,p) < D(i,k) + D(k,p) and\, j,k,p \notin tabu \\ k, otherwise \end{cases} \tag{9}$$

Node is the next node selected from node, node is the next node selected from node, an arbitrary node, a weighted adjacency matrix representing the complete graph, representing node and node. The distance between taboos is the taboo table.

(2) Order adjustment of the taboo list

In this process, the selection probability is to select the next node based on the shortest path of the adjacent node paths. With the above improvements, the method of selecting the next node for the two-step node shortest path strategy affects the transition probability. All nodes are added to the contraindications and the shortest distances are calculated sequentially in the contraindications tab. However, in this case, the distance calculated by the order of the nodes in the taboo tab is not necessarily the global shortest distance; in the later stage of the ant, the amount of pheromone on the path will become larger and larger, thus reducing the heuristic factor selection. If the ant has searched a non-optimal path before, the ant will follow this path. The search result is not a global optimum. Then the calculation formula of the adjusted path length is shown in formula(10):

$$j = \begin{cases} L(i) + D(R(j), R(j+1), D(R(i), R(j)) + D(R(j), R(p)) < D(R(i), \mathrm{R(p)}) + \mathrm{D(R(p), R(q))}, \\ L(i) + D(R(p), R(q)), otherwise \end{cases} \quad (10)$$

where R = tabu, record the best path for this iteration, represent the path length from the starting point to node i, and represent the distance from node to node in the tabu list. The main factor affecting them is the length of the path.

From the solution of the basic hybrid particle swarm multi-objective optimization algorithm, in the initial stage of the algorithm operation, since the information of each road section is the same, the ants can search for food sources without being affected by pheromone. Solved the problem, the effect is ideal, but solved the big problem, its operating efficiency is greatly reduced. Aiming at the defects of the basic hybrid particle swarm multi-objective optimization algorithm, an improved H method is given to reduce the shortcomings of the basic hybrid particle swarm multi-objective optimization algorithm as much as possible.

3. Experiment

3.1. Experimental dataset and experimental environment

In an intelligent decision support system, all data were calculated using Microsoft Core Studio 2010 software using a 4G memory laptop based on an Intel Core Duoi 5 processor. To illustrate the impact of the NS-ACO algorithm on dynamic TSP problems, this chapter introduces NS-ACO and AS, EAS, and combines MMAS, ACS, P-ACO and the recently proposed hybrid particle swarm multi-objective optimization algorithm (RIACO) with random immigration strategies were compared. RIACO is an effective way to increase population diversity by replacing ants in short-term storage with random migration. The six dynamic TSP base models used in this chapter are based on standard TSP instances in the TSPLIB library. Where eil51 and st70 represent small-scale TSP problems, while kroA100 and kroA150 represent medium-scale TSP problems. Kro A200 and pr299 represent large-scale TSP problems. TSP model is the most basic routing problem. Minimum path cost to the origin. This experiment adds a random flow factor to the six standard TSP instances to form a stochastic dynamic TSP problem. The upper and lower bounds of the random flow factor are set to 8 and 1, respectively, which makes the random flow factor possible. The frequency f of environment change is set to 10 and 100, respectively, indicating that the TSP environment changes every 10 iterations or every 100 iterations. They correspond to fast and slow changes in the environment. The magnitudes of environmental changes, m, are set to 0.1, 0.5, and 0.9, respectively, to represent low, medium, and high levels of environmental change. Therefore, for each dynamic TSP problem, the case can be further divided into 6 cases, that is, when C, there are 3 different levels of environmental changes, in order to systematically analyze the performance of various ant colonies o stochastic dynamic TSP optimization algorithms, A total of 36 practical cases are applied to 7 kinds of hybrid particle swarm multi-objective optimization algorithms. For the hybrid particle swarm multi-objective optimization algorithm in a certain case, the experiment will be run independently for 30 times, each iteration is 1000 times to ensure the reliability and validity of the experimental data.

3.2. Experimental steps

The higher the number of ants on the path, the higher the concentration of pheromones on the path, which leads to more ants choosing the path as food. To prevent ants from taking illegal paths, a taboo table is set up for them to record the paths they travel.

(1)Parameter initialization, Table 1 is the initial value of all parameters. Among them, the number of cycles of the parameters is generally 0, and the initial value of the pheromone is continuous.

Table 1: Initial value of parameters based on intelligent decision support system

Serial number	Parametric	Values
1	Times	$t = 0$
2	Number of cycles	$N_c = 0$
3	Initial value of pheromone	$\tau_{ij}(t) = \text{constant}$
4	Pheromone gain	$\Delta\tau_{ij}(t) = \text{constant}$
5	Maximum period	$N_{\max} = \text{constant}$

(2) Randomly assign ants to n cities, and then select city j according to formula (2), where j belongs, and C is the set of all cities.

(3) Modify the taboo form. Put the city j in step (2) into the taboo table.

(4) Repeat steps (2) and (3) until the ants complete all cities.

(5) Pheromone update. The pheromone on each path is updated according to equations

(6) If the iteration end condition N is reached, the loop ends and the result is output; if the end condition is not met, the pheromone volatilization factor is dynamically updated. Calculate the value of P by formula (5), and then clear the taboo table to prepare for the next cycle.

4. Discuss

4.1. Experimental Results and Comparison

Intelligent decision support system based on mobile communication. This paper simulates the basic hybrid particle swarm multi-objective optimization algorithm and the improved adaptive hybrid particle swarm multi-objective optimization algorithm at different scales. Among them, the basic mixed particle swarm multi-objective algorithm, when n=0, the average value is 2.6907, when n=30, the average value is 430.6789, this change is huge. The test results are shown in the table. "Average" indicates the mean of the sub-calculation results, and "variance" indicates the variance value of the optimal sub-calculation results. The optimal convergence curves and optimal paths of the two algorithms are shown in the figure. The "shortest distance" curve indicates that the optimal solution value changes as the number of algorithm iterations increases. The "average distance" curve shows that the average path length of all ants changes as the number of iterations of the algorithm increases. As can be seen from Table 2, whether it is a small-scale problem or a large-scale problem, the optimal solution of the improved adaptive hybrid particle swarm multi-objective optimization algorithm proposed in this paper is better than the basic hybrid particle swarm multi-objective optimization algorithm. At the same time, the variance of the improved adaptive hybrid particle swarm multi-objective optimization algorithm is also smaller than that of the basic hybrid particle swarm multi-objective optimization algorithm, indicating that the improved algorithm has higher robustness. As can be seen from the figure 2 to figure 4. The basic hybrid particle swarm multi-objective optimization algorithm and the improved adaptive hybrid particle swarm multi-objective optimization algorithm can obtain more reasonable travel routes for small-scale problems. However, for large-scale problems, the basic hybrid particle swarm multi-objective optimization algorithm has the phenomenon of path intersection, which means that the basic hybrid particle swarm multi-objective optimization algorithm cannot find a better path, while the improved adaptive hybrid particle swarm multi-objective optimization algorithm does not have a path. Crossover phenomenon. The proposed algorithm still achieves satisfactory results when solving large-scale problems.

In order to get the optimal parameter settings of the hybrid particle swarm multi-objective optimization algorithm in project management, we carried out this calculation experiment calculation object (if all 480 questions in the test set are calculated, the calculation time is not feasible. Because these 480 questions) with the same parameter settings for every 10 question instances. Therefore, in this calculation, we take the first problem and calculate 48 cases out of 10 problems. The number of ants and the number of cycles are 10. The rest of the parameters are set as shown in the table. As shown in Figure 3. A value with * indicates that the algorithm works best when the parameter takes this value. It is worth noting that the value of sum indicates that the search in the algorithm is a non-deterministic search; our interpretation of this is a non-deterministic search. Effectively expands the search space of the algorithm; note that the algorithm is the worst at the time. This shows the importance of heuristic information to the algorithm. The above analysis illustrates the effective role of the hybrid particle swarm multi-objective algorithm in research, and also shows the importance of heuristic information to the algorithm.

Table 2: Comparison of multi-objective algorithm and optimization calculation results based on mobile communication intelligent decision support system

Algorithm	Statistics	$n=10$	$n=30$	$n=50$	$n=80$
Basic Hybrid Particle Swarm Multi-Objective Algorithm	Optimum solution	2.6907	432.6819	456.6040	556.1862
	Average value	2.7098	430.6789	465.5456	567.4543
	Variance	0.0355	5.1897	5.7242	7.0578
Basic Hybrid Particle Swarm Multi-Objective Optimization Algorithm	Optimum solution	2.6907	423.7406	453.6789	553.6784
	Average value	2.6907	426.1334	459.1233	562.3424
	Variance	0.0045	2.3434	4.2131	5.2333

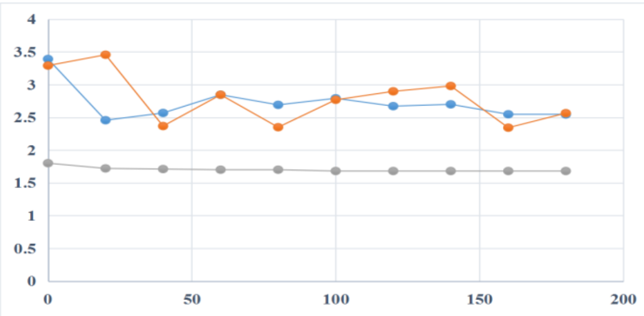

Figure 2: Based on intelligent decision support system, urban TSP adapts to people

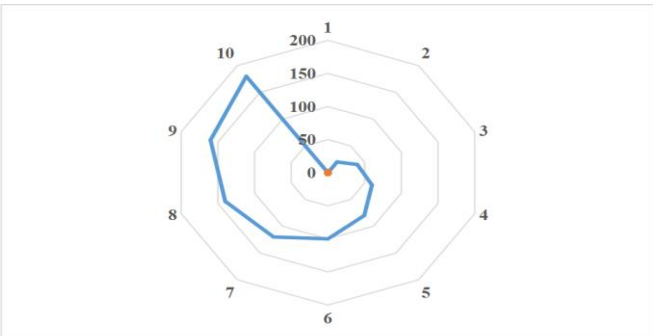

Figure 3: Convergence Curve and Optimal Path of Target Algorithm Based on Intelligent Decision Support System

4.2. Practical Cases in Project Management

In order to verify the feasibility and effectiveness of CAHBFO in solving RCPSP, this paper uses the project scheduling problem library (PSPLIB) widely used in academia to verify the performance of the algorithm. PSPLIB provides a dataset of four operations counts (excluding virtual operations), each using four renewable resources. Among them, j30, j60, and j90 all contain 480 instances, which are divided into 48 categories according to different parameters such as resource strength and network complexity resource factor. Each class also has 10 instances; j120 contains 600 instances, which are divided into 60 categories according to different parameter settings, and each category also contains 10 question instances. This chapter intends to select problem instances from different scales and compare them with other literature or basic bacterial foraging algorithms to verify the performance of the algorithm. For the problem database of the first type of process J=30, the problem instance j3010_1 is selected and solved by the basic bacterial foraging algorithm and the cloud adaptive hybrid bacterial foraging algorithm respectively. The total number of the four updateable resources R1, R2, R3, and R4 in the problem instance j3010_1 is 24, 23, 25, and 33, respectively. The specific item information list 3 is as follows:

Table 3: J3010 intelligent decision support system based on mobile communication_ 1 Project information

Processes	Models	Post-Processes	Duration	Resource Demand			
1	1	2, 3, 4	0	0	0	0	0
2	1	10, 11, 28	2	1	2	4	0
3	1	9, 15, 16	5	0	5	9	10
4	1	5, 6, 7	6	8	10	10	10
5	1	8	4	8	7	8	9

Statistical analysis can be performed on the results of 30 operations in Table 3, as shown in Figure 4 and Figure 5, comparing the results of 30 operations of the two algorithms and the calculated evaluation indicators:

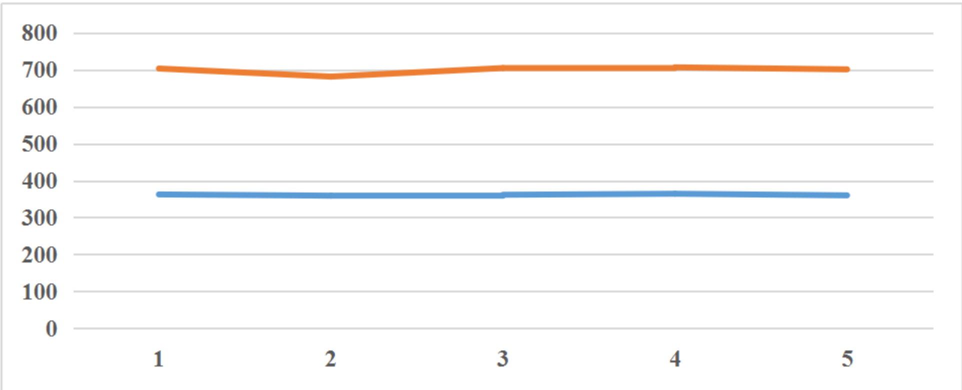

Figure 4: Algorithm comparison chart based on intelligent decision support system

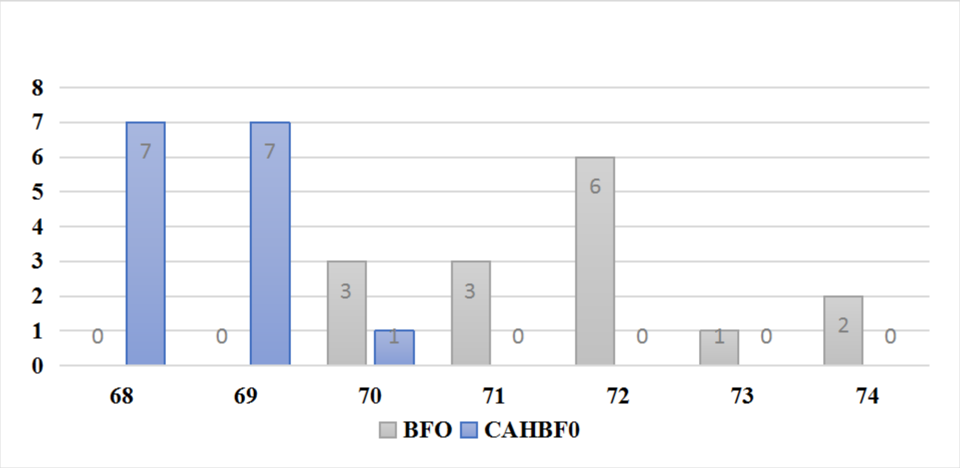

Figure 5: Optimal Duration of Two Algorithms Based on Intelligent Decision Support System

5. Conclusion

The work of this paper mainly focuses on the research of hybrid particle swarm multi-objective optimization algorithm and adaptive hybrid particle swarm multi-objective optimization algorithm in engineering supply chain management application research to obtain better hybrid particle swarm multi-objective optimization algorithm. On the basis of summarizing and studying the hybrid particle swarm multi-objective optimization algorithm and its improved algorithm, the adaptive mechanism is introduced into the hybrid particle swarm multi-objective optimization algorithm. The result of the hybrid particle swarm multi-objective optimization algorithm is that it is not easy to fall into a local optimum. Through careful introduction and analysis, a mathematical model that can be used to solve is established. And get the desired result. As the research focus, the adaptive hybrid particle swarm multi-objective optimization algorithm is described in detail. In particular, the pheromone is adjusted and optimized, and the switch model is optimized through the division of labor mechanism. And through the simulation of the optimization algorithm, the corresponding simulation results are obtained.

Project engineering itself is a very traditional industry, but project engineering supply chain management is indeed a very new topic and a hot topic and topic in recent years. Of course, with the implementation of the national energy conservation and emission reduction policy and the fierce competition in the industry, especially the rise of the concepts and project management of some excellent foreign engineering companies, it has had a considerable impact on the domestic project management model and project management. How to use more cost-effective and efficient projects to complete the work of the country and the owner is particularly important and has become a major issue. And a more optimized engineering supply chain management system is more important for countries and companies to compete in the international environment and business. Mobile communication intelligent decision support system plays an important role in project management.

Based on actual project management experience, especially warehouse management to installation and delivery, as well as the use of optimization algorithms, this paper has theoretically produced optimization results and achieved quantifiable practical significance, which is very enlightening and helpful for future work. . In the actual project supply chain management, there are still many places that can be optimized and improved. Of course, this also requires more time to be researched in future work, and it is constantly proved through practice. At the same time, we must also see some problems. Just as the algorithm itself needs improvement and refinement, there are some problems in practical application. For engineering projects, for example, there are still many uncertainties. For example, suppliers have a high defect rate at a particular time, which is difficult to predict before project execution or mathematical modeling. For example, for some commercial projects, it is also a very important question whether such simulation optimization calculation can convince your investors. It should be noted that the above work is an arduous and long process, which requires the continuous efforts and systematic research of many researchers. It is believed that with the deepening of research, the hybrid particle swarm multi-objective optimization algorithm and engineering supply chain management problems will achieve great results and be fully developed and applied. In summary, the use of particle swarm optimization algorithm analysis is an expansion of its application scope and an in-depth discussion of the research object of this paper.

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