

Role Mechanism of Enterprise Management Efficiency Improvement Based on Improved Drosophila Algorithm

Hui Wang^{1,*}

¹ Shandong Electric Power Engineering Consulting Institute Corp., Ltd., Jinan 250100, Shandong, China

Abstract

INTRODUCTION: With today's intelligent technology in full swing, many companies and enterprises need to catch up to the reality of internal management. To make the company better adapt to society and realize its sustainable development, it is essential to optimize the internal management means and improve the management efficiency of the enterprise.

OBJECTIVES: To find the optimal staff allocation scheme and the best decision path by utilizing the improved fruit fly algorithm and establishing the enterprise's regular task and staff allocation model.

METHODS: We analyze the standard swarm intelligence algorithms, and then we compare the differences between the basic fruit fly algorithm, the optimized fruit fly algorithm, and the above swarm intelligence algorithms. The fruit fly algorithm is utilized, and the algorithm is optimized to fit the actual enterprise management model. At the same time, the influence of Levy's flight on the Drosophila algorithm in enterprise management efficiency improvement is studied. Finally, it points out the application fields, the optimized Drosophila algorithm's current situation, and the existing problems and shortcomings.

RESULTS: By comparing the performance of the Drosophila algorithm with that of the other three optimization Drosophila algorithms, the influence factors of Levy flight on the enterprise's internal management allocation are obtained, making the algorithm a good fit for the model. The results of the optimal allocation scheme under known conditions and the best decision were obtained.

CONCLUSION: The experimental results show that the optimized fruit fly algorithm can solve the multi-parameter allocation problem of enterprise management, which has high reference value and significance for general enterprise internal management.

Keywords: fruit fly optimization algorithm, business management, efficiency improvement, management innovation

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*Corresponding Author. Email: 20735282@qq.com

1. Introduction

Nowadays, with the continuous development and innovation of artificial intelligence as well as big data technology, all walks of life in society are facing the problem of transformation and upgrading industries to intelligentization. In today's enterprises, in the face of reform and opening up, the internationalization of the market is only possible through the output of traditional commodities, whose profits maintain the development of

enterprises. The key to breaking the game can be to improve the company's or enterprise's internal operation and management efficiency, further reduce the operating costs, inject new momentum into the development of enterprises, and at the same time, ensure that the management structure and management mode adjustment are conducive to the long-term development of the whole enterprise(Zeng & Hanyue, 2021). Therefore, the improvement of enterprise management efficiency for the enterprise itself can be two birds with one stone. The improvement of the management efficiency of the

enterprise itself can be multi-faceted, including but not limited to the enterprise's daily operation of the process of business philosophy, the enterprise's internal management methods and management processes, the enterprise's daily operation of the production model, the product marketing tools, and the business model upgrade. In today's increasingly competitive market, the efficiency of an enterprise's internal management determines the future development of the enterprise's long-term power. With the current artificial intelligence technology, big data cloud computing can help enterprises strengthen internal management (B et al., 2021). In this context, there are new possibilities and means to improve the internal management efficiency of enterprises.

2. Research Background

A survey and study of the management styles of most companies in the market are summarized as follows: Although most companies. The management style of the overall development of their existence has certain specificities. However, a prominent problem is that this part of the enterprise's management concept needs to catch up (Dudycz et al., 2021). These lagging management concepts are often based on the empiricism of the previous domestic or foreign successful enterprise management and operation modes of simple imitation but did not combine with the specificity of their industry and the latest development of the market changes, and therefore, in the current reform and opening up as the theme of today, it is not easy to have a breakthrough and development. In imitating and copying successful enterprises, there are problems such as the uneven management ability of the management personnel at all levels of the enterprise and the confusing scope of the independent decision-making power owned by each level, Etc. These problems will have a severe impact on the long-term development of the enterprise. These problems will seriously affect the regular operation of the enterprise in the long run, and the productivity and management efficiency of the enterprise will also decline. In addition, part of the enterprise's long-term management mode is unchanged, resulting in the organization's internal management becoming rigid and reducing the adaptability of any innovative management mode. At the same time, it is difficult for employees and managers to make innovative suggestions that benefit the enterprise's development. This leads to a certain degree of closure in the internal management of the enterprise, which further reduces the overall vitality of the enterprise. In enterprise management personnel construction, many enterprises have talent training modes (Legenchuk et al., 2021). The enterprise's reserve strategic management talent capacity needs to be higher. For the training of employees within the enterprise, career planning and other systems are set apart from the actual situation of the development of the enterprise sector, resulting in the inability to play out the ability and level of departmental applications. In addition,

the development of employees is also better. For enterprises to deal with the progress and efficiency of daily affairs, they cannot be significantly improved. In today's rapid technological development and increasingly fierce competition, the customer groups faced by enterprises are no longer a single fixed group of people, and the business dealt with by enterprises is also constantly changing. The company's development certainly has new opportunities and challenges in this context. With an emphasis on innovative talents and rational coordination of task distribution between departments, when the enterprise encounters an urgent emergency, it can be more flexible in its response and increase its resistance ability.

The primary algorithm used in this paper is the Fruit Fly Optimization Algorithm (FOA) (Akhtar et al., 2021). The primary fruit fly algorithm is a group intelligence algorithm. In recent times, scholars have summarized the particular laws of the behavior of animal groups in nature. The FOA was proposed as a new theory in the 1990s by Italian scholars to study the problem of how ant colonies find the shortest path from themselves to food. In the following decade, other scholars have been inspired to propose the specifics and requirements of swarm intelligence algorithms. Optimization techniques for colony intelligence algorithms can be approached in two ways. Firstly, they use mathematical methods such as taboo search or hill climbing algorithms.

Limited conditions can be explored regarding this type of optimization technique. So, some scholars turn to optimization techniques through natural phenomenon heuristics to propose further optimization schemes. Natural heuristics can also be divided explicitly into natural biological and heuristics that simulate physical or chemical natural phenomena. Specific techniques for the latter include simulated annealing algorithms and acoustic search algorithms (Vladimir et al., 2022). Biological heuristics has three main types of techniques: evolutionary computation based on organisms, like genetic algorithms or evolutionary planning algorithms; algorithms based on group intelligence; and other types, like cultural algorithms or immunity algorithms of organisms (Oszust et al., 2021). The fruit fly algorithm is a group intelligence algorithm. Inspired by the foraging behavior of the fruit fly, Taiwanese scholar Pan Wenchao proposed an algorithm with a simple computational process and easy-to-understand logic. The swarm intelligence optimization algorithm is a standard computational intelligence algorithm. The basic theory of this algorithm is derived from the simulation of animal behavior in nature, such as the behavior of bee swarms, wolf packs, and fish packs. Through the exchange of information and cooperation between groups, the purpose of integrating and optimizing information is achieved through the limited interaction of individuals (C. Li et al., 2022). Compared with individual intelligence, group systems are mainly based on simple rules and a limited number of individuals to achieve information transfer and optimization, and the individuals need a more

sophisticated logical structure and design. The advantages of group intelligence are strong robustness, low influence of the system on external interference, strong adaptability, and stability. The most important research problem in group algorithms is the optimization problem. Unlike traditional algorithm optimization, the algorithm optimization of swarm intelligence is mainly based on biomimicry, a probabilistic parallel global search algorithm, to achieve faster search speed and search for the global optimal solution of complex problems. Standard population intelligence optimization algorithms include Ant Colony Optimization (ACO), Water Wave Optimization (WVO), Fireworks Algorithm (FWA), Grey Wolf Optimization (GWO), GWO Optimization, Shuffled Frog Leaping Algorithm (SFLA). These population intelligence algorithms are mainly used in finding the optimal value of a function, solving the traveler's problem, multiprocessing scheduling problems, problems of dependent optimization, and job scheduling problems. Drosophila is an organism with excellent sensory perception, especially in olfactory and visual performance. Relying on its unique olfactory organs, Drosophila can sensitively detect various odor molecules floating in the air and even detect food tens of kilometers away (Pradhan et al., 2023). When the fruit fly searches for the source of food, it can pinpoint the exact location of the food and the gathering direction of its companions by using its sensitive visual organs. Scholars at home and abroad have thoroughly researched the fruit fly algorithm's optimization. There is multi-directional in-depth research for the theoretical analysis of the algorithm and optimization and improvement of the algorithm at the application level. In addition to the optimization algorithm used in this paper, scholars have also proposed using simulated annealing to adjust the optimal position of Drosophila individuals after the Drosophila enters the iteration. The advantage of this optimization algorithm is that it can be adjusted for objects with poor individual sequences, similar to the barrel effect, improving the accuracy of the algorithm's results. Research on the fruit fly algorithm is currently focused on computer science and technology for the adaptive convergence accuracy of supportable vector neural networks to achieve group intelligence. There is also room for application in electrical engineering—for example, identifying faults in distribution grids and hydroelectric units in the power market. In control science and engineering, least squares support vector machines and local regression neural networks are used for parameter identification in PID control (Kumar & Sikander, 2021). In mathematics, Drosophila optimization algorithms enable global convergence of mathematical models, parameter estimation optimization problems and the optimization of mathematical models. In mechanical engineering, using Drosophila optimization algorithms, one can perform parameter and fault diagnosis or optimization to solve rolling bearing and rolling specification hysteresis problems. Finally, in mining engineering, it is possible to predict mining transportation in tailings ponds safely.

3 Research Methods and Materials

3.1 Common Population Intelligence Algorithms

Many organisms in nature have the attribute of population, and organisms with this attribute can realize the sharing of information interoperability on a population basis. Take an ant colony as an example; the behavior of individual ants does not have multiple purposes. However, for the behavior of the whole colony, there must be some natural law governing it. Another example is a flock of geese in flight lined up in the shape of a "human". This pattern not only provides an adequate warning of danger for the entire flock but also effectively increases the speed of the flock and saves energy. There are many other examples of this phenomenon in nature. The concept of group intelligence originated from observing the behavior of living creatures in nature. For example, a single fruit fly does not have a very sophisticated physiological structure that can support it in realizing complex behaviors and accomplishing complex tasks, which is the core feature of intelligent algorithms in biological populations (Auwul et al., 2021). However, the entire fruit fly population can build up a large nest of fruit flies through the division of labor and information exchange between individual fruit flies. We can distill some essential information to build a theoretical model responding to this behavior. First, there are rules in the model that govern the behavior of all individuals, and each individual will follow them unconditionally. Second, all units in the model are similar in structure and function, so the division of labor for the same attribute is clear. Finally, all individuals can collect simple information, and information transfer and communication can be realized between individuals (Ye et al., 2021). This behavior determines the direction or content of the subsequent behavior of the whole population. Scholars have abstracted the above into five principles: adaptability, stability, quality, proximity, and diversity. The five principles of group intelligence are summarized in Figure 1.

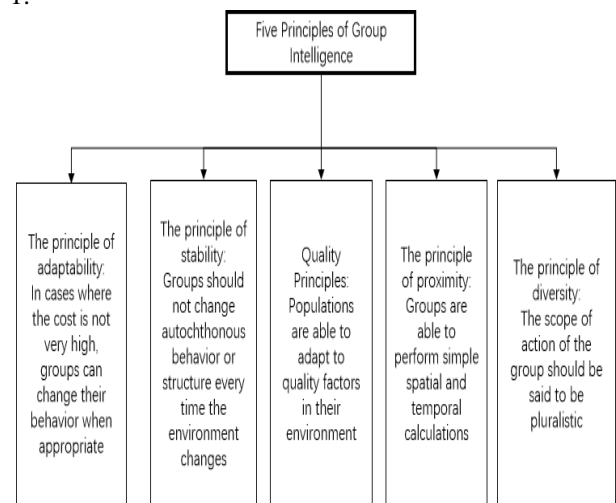


Figure 1: Five Principles of Group Intelligence

The above five principles are briefly explained here: (1) principle of proximity: it means that the group of organisms can carry out simple spatial and temporal calculations for the surrounding environment; (2) principle of quality: it means that the group can accurately recognize the quality factors in the environment and react correctly in a timely manner; (3) principle of diversity of response: it means that the response to external changes at the group level is not single but diverse; (4) principle of stability: it means that the group has a certain degree of robustness to slight changes in the external environment and will change only when it cannot adapt, rather than when there are slight changes in the environment. and diverse; (4) the principle of stability: that is to say, the group has a certain degree of robustness to slight changes in the external environment, but only in the case of an inability to adapt to change rather than in the case of slight perturbations in the environment; The principle of adaptability posits that a group should possess the ability to respond to changes in the external environment without incurring significant costs associated with internal modifications. This enables the group to make appropriate adjustments as needed. As long as any biological population contains the above five principles, it indicates that the main body of the population has a strong ability to adapt to the environment and can effectively integrate the collected information and make corresponding adjustments to its behavior. In the development of computer science, the arithmetic power of hardware equipment is constantly improving, and various theories are constantly improving, which has created the possibility for the realization of many biological population algorithms(Huang & Zhang, 2022). At present, the mainstream swarm intelligence algorithms mainly include the ant colony algorithm proposed for the ant colony's foraging behavior, the immunity algorithm proposed for the working principle of the individual immune system of biological organisms, and the fish swarm algorithm proposed for the foraging behavior of fish swarms, tail chasing behavior.

(1) Ant Colony Algorithm: The biological principle of this algorithm is to mimic the process of searching for food by an entire colony of ants. The process has the following characteristics: First, ants can release chemical pheromones to mark themselves independently. Other ants use the chemical pheromone marked by individual ants to distinguish the general direction of food. Since the chemical pheromone will be volatilized in the air, the exchange of information between ants will continuously increase the concentration of chemical pheromone in the direction of food. When the concentration of the chemical pheromone increases in a specific direction, it indicates to the colony that there is food in that direction. The advantage of this algorithm is that it has objective-solving solid ability, and multiple locally optimal solutions can be obtained simultaneously through a positive feedback mechanism similar to a chemical pheromone. By introducing a probabilistic search, the algorithm can avoid the dilemma of having local optimal solutions. Relying on

the advantages of this algorithm, the ACO algorithm is widely used in problems such as vehicle scheduling and the design of integrated circuits.

(2) Immune algorithm: The biological theory of this algorithm is the imitation of the immune system of living organisms. The algorithm has an excellent ability to find the global optimal solution. However, the accuracy of its algorithm requires a high degree of precision, and at the same time, its algorithm is more complex with many parameters. The application of this algorithm is relatively tiny.

(3) Fish Swarm Algorithm: The biological theory of this algorithm is to simulate the behavior of a school of fish that needs food. The difference between the fish swarm algorithm and the ant colony algorithm is that each fish does not accept unified management, and all the behaviors are individual, so a single individual's survivability is extreme. Therefore, from the point of view of the algorithm, the fish swarm algorithm has a higher space complexity but excellent global optimization ability and robustness. At the same time, the fish swarm algorithm does not depend on the initial value or internal parameter selection.

Although there are many types of group intelligence algorithms, different rules and parameters must be constructed to imitate the behavior of different organisms. Individual populations have different internal organizational structures. However, the five basic principles of group intelligence can be used to abstract the main processes of group intelligence algorithms: First, initialize the parameters of the target group and assign values to the parameters in the algorithm; second, define the adaptive function and compute the initial solution, and set up a specific way of solving the target problem, and then iterate the algorithm by the rules of the set population, and if the data after iteration meets the set conditions, then it can exit the loop. If the data after the iteration reaches the set conditions, the loop can be exited; otherwise, continue to iterate until the conditions are met. Set the loop conditions, which can be a specific number of iterations, a parameter threshold, and finally, output the data at the end of the algorithm. The general flow of the specific swarm intelligence algorithm to solve the problem is shown in Figure 2.

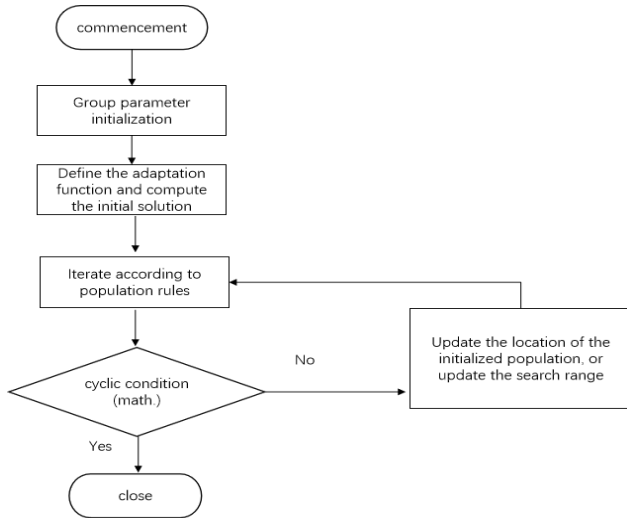


Figure 2: General flow of the swarm intelligence algorithm to solve the problem

3.2 Basic and Optimized Drosophila Algorithms

Inspired by the behavior of biological populations in nature, benchmarking in the field of computers, and computational group intelligence calculations

The method effectively simulates the behavior of natural biological populations. It can be concluded through the study of a specific biological population that by utilizing the large number of individuals in the population and the exchange of information and hulls between individuals, even the limited information collection ability of simple individuals can perform very well at the macroscopic level. In addition, the advantages of the population intelligence algorithm are concentrated in the simple logic of the algorithm, which is easy to operate and process. At the same time, the processing effect is also ideal. Currently, the algorithm is widely used in scientific data calculation, economic management, and other fields. The Drosophila algorithm used in this paper first needs to initialize the position of the Drosophila population. We use $InitX_axis$, and $InitY_axis$ is represented. This allows for the representation of Drosophila food searching behavior, where the random direction and length of distance in which Drosophila find food are calculated from this information about olfaction.

The two-dimensional coordinate method is used to represent the location of the fruit fly population. The food location is expressed on the two-dimensional coordinates, where the horizontal coordinate is the sum of the initial horizontal coordinates of the fruit fly population and the random value. The vertical coordinate is the sum of the initial vertical coordinates of the fruit fly population and the random value, and the equation is expressed as follows:

$$X_i = X_axis + RandomValue \quad (1)$$

$$Y_i = X_axis + RandomValue \quad (2)$$

In the actual situation, it is impossible to get the target's position information in advance, so the initial position distance of the target from the total population of fruit flies is first predicted as D_init . Then, the judgement value of the odor concentration is calculated as S_init . When the odor reaches the judgement value, the direction of the finding can be approximately correct. The distance between the food's predicted location and the Drosophila population's location in two-dimensional coordinates is D_init , which is obtained as the square difference between the sum of squares of X_i and Y_i obtained from equations (1) and (2). The flavor concentration is inversely proportional to the distance, i.e., the closer the distance, the more robust the flavor and the larger the value, and the farther the distance, the lighter the flavor and the smaller the value. The equation is given below:

$$D_init = \sqrt{X_i^2 + Y_i^2} \quad (3)$$

$$S_init = \frac{1}{D_init} \quad (4)$$

In order to represent the location of the flavor concentration of a single Drosophila individual, the parameter $Smell$ is at this moment, which is computed using the odor concentration determination function. The function takes the flavor concentration S_init as a parameter and calculates the flavor concentration of an individual fruit fly. From this, it is possible to obtain the concentration at the location of all individuals in the fruit fly population. Based on this data, it can be concluded that the individual's position in the group is the one with the highest flavor concentration, which is used to update the flight direction of the fruit fly. Finally, all the above steps are looped again, and a suitable flavor concentration threshold is set. After this threshold is reached, the loop is exited, i.e., the flight is terminated, and finally, the food location is obtained. With the further application of the Drosophila algorithm, many problems of the Drosophila algorithm are exposed, such as the fact that the basic Drosophila algorithm is weak in the global search of data and in the process of carrying out many iterations, problems such as convergence speed being too fast, time is too early. The accuracy of convergence needs to be improved. In addition, population diversity is also easily constrained by the global search ability of the algorithm. The current optimization of the Drosophila algorithm includes regulating Drosophila population diversity and adjusting the algorithm's search step size. Finally, some scholars have also proposed mixing the Drosophila algorithm with other algorithms to make up for the search defects of the Drosophila algorithm by complementing each other's strengths and weaknesses.

The optimization of the basic Drosophila algorithm in this paper focuses mainly on the following aspects: The first is the adaptive adjustment of the Drosophila flight step length. In the period when the algorithm starts to run, increasing the step length can effectively shorten the running time of the algorithm and further accelerate the

speed of data convergence, and this step has no substantial effect on the accuracy of obtaining the global optimal solution. Because the basic Drosophila algorithm mainly uses this method, it can effectively solve the problem of the low global search ability of the Drosophila algorithm. Secondly, compared with the primary fruit fly algorithm, the optimization algorithm introduces a new parameter based on S_{init} . This parameter mainly plays a role in the late running of the algorithm; in the late execution of the algorithm, many local optimal solutions will appear. Introducing the parameter reduces local optimal solutions' influence and improves the accuracy of finding the global optimal solution. In summary, the optimized Drosophila algorithm has stronger robustness, and the speed of finding the global optimal solution is effectively improved. In addition, the optimized algorithm also obtains higher data accuracy, mainly because the optimized algorithm introduces new parameters at the later stage of many local optimal solutions achieved by the basic algorithm to avoid the basic algorithm falling into the dilemma of local optimal solutions.

3.3 Model Construction of an Optimized Drosophila Algorithm in Business Management

In the conceptual abstraction of enterprise management to build a model, assuming that the enterprise development process can be put into the management of the cost of R, the actual development of the enterprise cost overhead function can be mainly abstracted as $R = \{ \text{human resources H, input capital F, and time T} \}$. That is, in the limited cost and various constraints, to achieve the optimal solution to achieve a reasonable allocation of resources and improve enterprise management efficiency. The final efficiency of the enterprise is denoted by E, which is related to the competitiveness P and the profitability of the enterprise's business G. It is expressed by the abstract function $E = (P, G)$, where R_n denotes the number of available resources owned by the enterprise.

$$\begin{aligned}
 P > 0 \\
 P &= (r_1 \times w_{1,1} + r_2 \times w_{1,2} + \dots + r_n \times w_{1,n}) \\
 n &= |R|
 \end{aligned}
 \tag{5}$$

The optimized Drosophila algorithm using Levy flights focuses on positional updates for individual Drosophila. The main element is the introduction of the Random Value parameter to the basic Drosophila algorithm. This parameter modulates the algorithm's global optimization capability (Jiaming et al., 2022). However, attention should be paid to the initial setting of the Random Value parameter, whose value range is usually a random number between the constants a and b. If the initial setting of the parameter is not appropriate, the algorithm will enter the local optimal predicament in the initial iteration. Therefore, the algorithm's ability to achieve global and local optimization should be reasonably balanced. The use

of Levy's flight randomization at the beginning of the iteration of the Drosophila optimization algorithm can increase the ability of the algorithm to find the global optimum and avoid the risk of the algorithm falling into a locally optimal solution. After this stage, the random value of random values is used further to find the local optimum within a limited accuracy range. The primary process of the algorithm is as follows: according to the enterprise management model established in this paper, the practical problem solved is summarized as the ability to find the global optimum under multiple parameters. Step 1: Initialize the parameters, determine the maximum number of iterations of the algorithm, and determine the threshold of the population size, in addition to the number of parameters and the dimension of the population. The two-dimensional coordinates of the initial population are determined, and a two-dimensional coordinate represents all subsequent fruit fly locations. Step 2: The algorithm starts going into iterations, and as the number of iterations keeps increasing, the algorithm gradually starts traversing the entire population. Step 3: After the number of iterations reaches a threshold, the position of the population needs to be corrected by updating the position of the population and dealing with changes in the flavor concentration values. Steps two and three are repeated until all populations are traversed, and a local optimal solution is found. The results need to be saved after each globally optimal solution is obtained. After each facilitation, the global optimal solution is compared with the results of previous facilitations, and the global optimal solution is continuously updated. If the number of iterations reaches the specified threshold, the algorithm is exited, and the optimization search is terminated. The specific flow is shown in Figure 3.

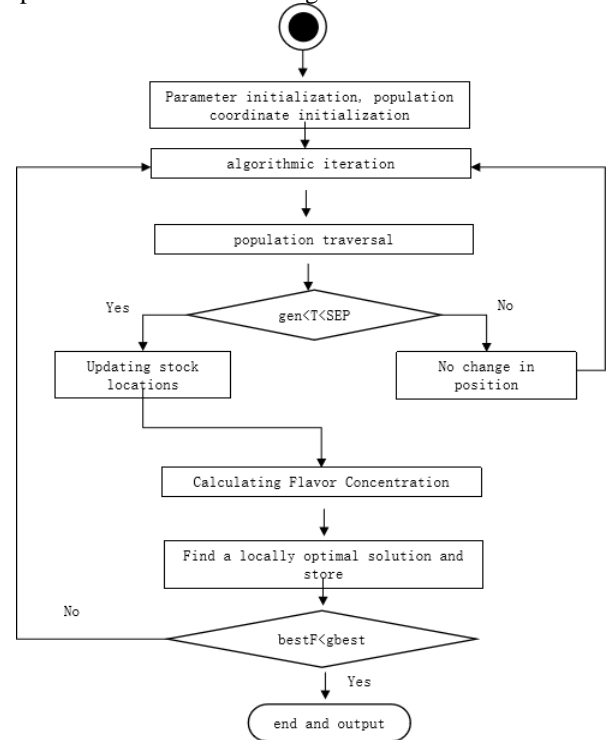


Figure 3: Flowchart of the Optimized Drosophila Algorithm

4. Results and Discussion

4.1 Analysis of the time complexity of the optimized Drosophila algorithm

For any algorithm, its time complexity consists of the time taken to run the various control structures in the algorithm. The dimension of the number of times some primitive operations that make up the basic Drosophila algorithm are executed in the algorithm affects the algorithm's time complexity. Therefore, to measure the algorithm's time complexity, three test functions are chosen to measure the time complexity of Levy's flight optimization Drosophila algorithm (Shan, 2022). Before starting the test, the size of the population was set to 25 in the initial parameters, the algorithm was iterated for a total of 100 times and repeated independently ten times, and the time taken by the algorithm to run at dimensions 100 and 200 was calculated as the average time taken to run the algorithm. From the following Figure 4, it can be concluded that, compared with the primary fruit fly algorithm running time, Levy flight optimization of the fruit fly algorithm ran longer and did not open a big gap, so the time complexity of Levy flight optimization of the fruit fly algorithm used in this paper is feasible.

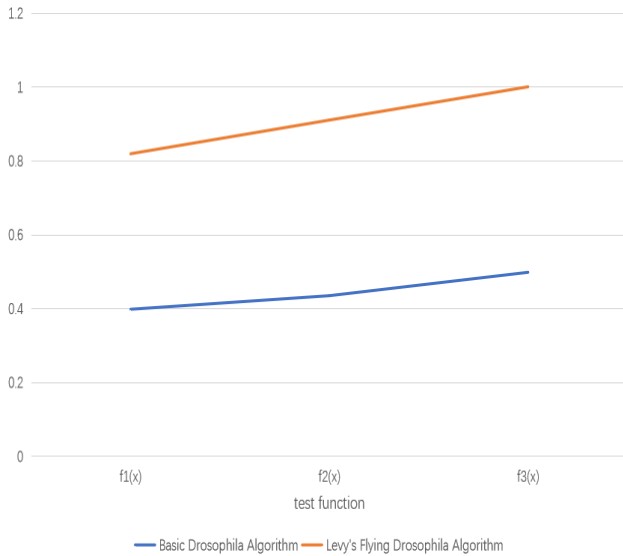


Figure 4: Comparison of the time complexity of the basic Drosophila algorithm and Levy's flight-optimized Drosophila algorithm

In order to verify the performance of the Levy flight optimization Drosophila algorithm, the size of the problem to be solved is now set to $m \times n$, the size of all populations is 25, and the total number of iterations of the algorithm is 250. In order to exclude the randomness of the experimental data from generating relevant errors, the data results are now processed using the statistics

principles to calculate the variance and mean of each repeated execution. From the obtained data, it can be determined that the optimized Drosophila algorithm using Levy flight is smaller than the basic Drosophila algorithm in terms of variance, which indicates that the optimized Drosophila algorithm using Levy flight is more robust in solving different problem sizes. At the same time, the final results obtained are more accurate (Haiying, 2021). It intuitively indicates the feasibility of this optimization algorithm. The performance comparison between the basic Drosophila algorithm and the Levy flight optimization Drosophila algorithm is shown in Figure 5.

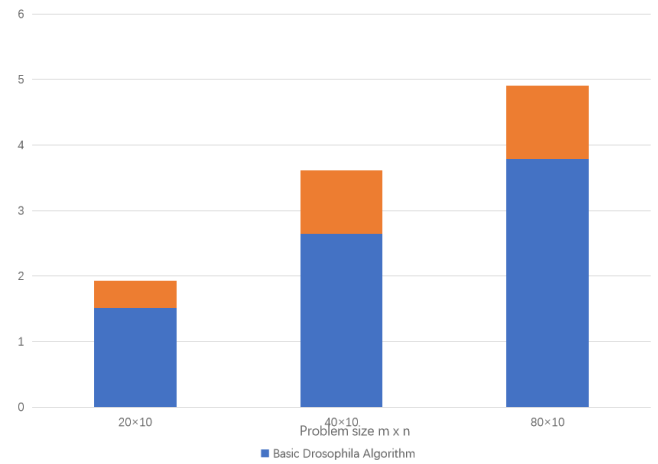


Figure 5: Comparison of the Performance of the Basic Drosophila Algorithm and the Levy Flight-Optimized Drosophila Algorithm

The process concerning the optimization of the Drosophila algorithm can be divided into two inner and outer loops. The outer loop controls the number of iterations of the algorithm. In contrast, the inner loop ensures that all populations can be traversed to ensure that a global optimum emerges from the number of iterations (Yamamoto, 2021). The use of Levy flights to update the position of the populations at regular intervals does not affect the algorithm's structure and, therefore, has no impact on the algorithm's time complexity. The inner and outer loops mainly control the time complexity of the resulting optimized Drosophila algorithm. Assuming that the number of iterations of the algorithm is T and the number of populations is N , the time complexity of the whole algorithm can be expressed as $O(N \cdot T)$. The algorithm's time complexity is $O(T \cdot T)$ when and only when the number of iterations and the number of populations are the same. Also, the SEP threshold size affects the result of the algorithm's global optimum finding. In this paper, we mainly set the threshold SEP value as 0, 0.2, or 0.5 and compare and analyze the impact of different thresholds on the final results of the algorithm from the three perspectives of the average, standard deviation, and the optimal value of the final results of the algorithm. When the threshold value is set to 0, i.e., the effect of Levy's flight action is 0, the algorithm is the basic Drosophila algorithm (Xia, 2021). Figure 2 shows that the algorithm's performance in the

three parameters tends to be stable, but the accuracy of the optimal value is the lowest among the three values. When the threshold is set to 0.2 or 0.5, levy flights are used, and levy flights are used to varying degrees. As shown in Figure 2, the standard deviation of the thresholds is slight at 0.2 and 0.5, and the difference in the optimal value is not very large. The effect of different thresholds on the algorithm's optimization results is shown in Figure 6.

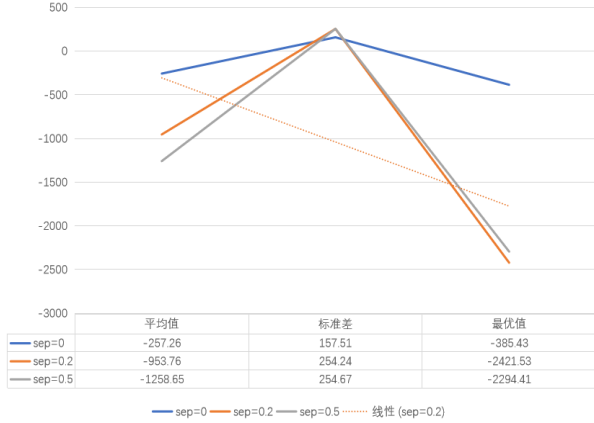


Figure 6: Effect of different thresholds on the algorithm optimization results

4.2 Comparison of the Drosophila algorithm using Levy flight optimization and other optimization algorithms

In this paper, Levy flight is used to optimize the fruit fly algorithm, and the fruit fly algorithm based on chaotic step size optimization (CSFOA) and the optimized fruit fly algorithm based on exponentially decreasing step size (TEFOA) are chosen for comparison(J. Li et al., 2021). First, in terms of parameter setting, Levy's Flying Optimization Fruit Fly Algorithm involves five parameters, which are A, B, C, N, and T. All of them have different degrees of influence on the algorithm's search for the global optimal solution for the Optimization Fruit Fly Algorithm. The parameter N represents the overall number of iterations of the algorithm, and the parameter T represents the algorithm's running time. The algorithm's running time will directly affect the size of the Drosophila population, which is manifested in the breadth of the actual Drosophila distribution range. As a result, parameter T and parameter N affect both the accuracy with which the program is run and the efficiency with which it is run. Although these four parameters influence the iterative step size of the algorithm, they adjust the range of the algorithm to find the optimal value, thus affecting the accuracy of the algorithm's running results. In this paper, the initial settings of these four parameters are $A=C=init/10$, $N=45$, and $T=5000$.

The number of iterations of other Drosophila optimization algorithms and the algorithm's running time are consistent with the parameters of Levy's step-size optimization Drosophila algorithm. For the measurement of excellent and lousy algorithm running results, in this comparison,

we mainly look at two indicators of the three algorithm running results: the accuracy of the algorithm running. For example, to avoid the algorithm's impact in running data randomness on the algorithm's results, the algorithm uses the average (AVG) as the final judgement after several runs. If the average value is small, it reflects that the algorithm's ability to find the optimal solution globally is strong, and the accuracy of the result is higher. In addition, the stability of the algorithm also needs to be considered. The data variance indicates the algorithm's stability during the algorithm's operation. When the data variance of the algorithm is more minor, it indicates that the algorithm's stability is better. A comparison of the three Drosophila optimization algorithms is run, and the final results obtained indicate that the average results of the Levy flight optimization Drosophila algorithm are the same as the optimization Drosophila algorithm based on exponentially decreasing step size in terms of algorithmic stability and algorithmic accuracy due to the use of the chaotic step size optimization algorithm. The data for comparing the Levy flight optimization Drosophila algorithm with other optimization Drosophila algorithms are shown in Figure 7.

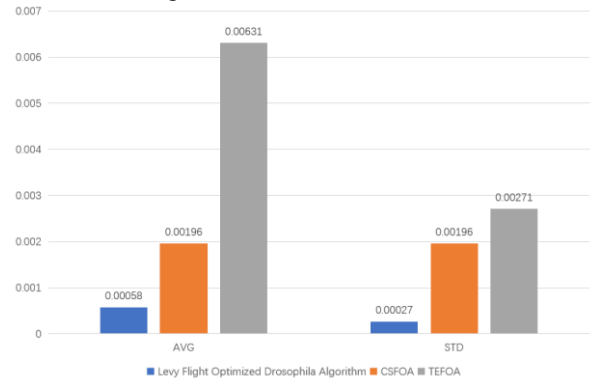


Figure 7: Comparison of Levy's flight-optimized Drosophila algorithm with other optimized Drosophila algorithms

During the actual testing of the algorithm, it was found that the presence of the third parameter, B, slightly perturbed the algorithm's ability to find the final global optimal solution. Therefore, to analyze parameter B's effect on Levy's flight optimization Drosophila algorithm, parameter B is taken as (1.00, 1.25, 1.50), and the size of the other parameters is fixed. In this round of testing, parameter B was used to execute the algorithm 50 times in the face of different numbers of iterations and population sizes, which was ultimately measured as the average of the RMSE(Akenbor & Nwandu, 2021). The horizontal coordinates of the graph indicate that the number of iterations and the population size of the algorithm are taken to the same value. When the value of parameter B is taken ten times, it has less impact on the convergence speed of the algorithm as well as the accuracy of the final search results (Jouida B, et al., 2021). When the number of iterations is 5, and the parameter B is 1.0, the mean value of RMSE is the largest of the three. Therefore, the value of the parameter should

be around 1.0. The effect of different values of parameter B on the Levy flight optimization Drosophila algorithm is shown in Figure. 8.

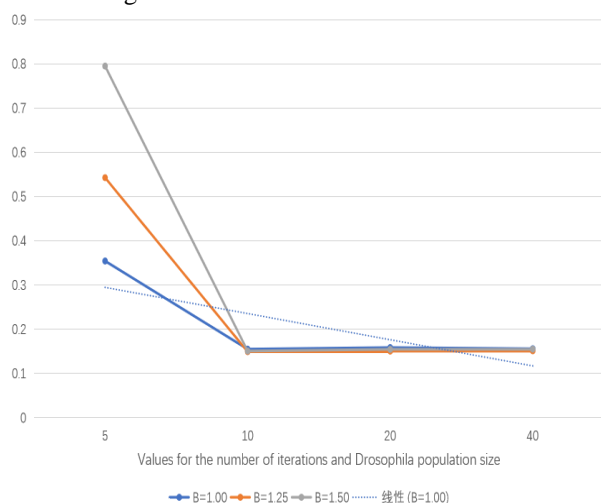


Figure 8: Effect of different values of parameter B on the Levy flight optimization Drosophila algorithm

In the era of economic development and global integration, the competition among enterprises is becoming increasingly fierce (Narsimha G, et al., 2021). The sustainable development of enterprises relies on the previous management experience and system and needs to innovate in technology and management. Moreover, nowadays, the knowledge economy is being emphasized by more and more people, and it is not easy to support the long-term development of the whole enterprise by simply relying on the profits generated from previous product sales or product services. Therefore, this paper proposes using a swarm intelligence algorithm to help improve the management efficiency of enterprises. Based on the primary fruit fly algorithm, it is proposed to use Levy flight to correct and update the position of the population, expand the search range of the fruit fly population, and avoid the algorithm from affecting the convergence effect of the data by fixing the position of the population in the running process. Finally, the problem of optimal redistribution of resources under various conditions and requirements in enterprise management is solved. After the above discussion, it can be concluded that the basic fruit fly algorithm has many problems. For example, the overall convergence speed of the algorithm is slow, the accuracy of the results is not high, and the experimental results obtained in the end have a certain probability of a locally optimal solution rather than a globally optimal solution.

5 Conclusion

In this paper, we conduct theoretical abstraction and conceptual modelling for practical problems arising in the enterprise management process and use Levy flight to determine random numbers to update the position of the fruit fly population. By optimizing the step length of the

primary fruit fly algorithm and the correction of the flavor concentration determination, the algorithm's accuracy is effectively improved, and the final result avoids falling into the dilemma of a locally optimal solution. The algorithm's time complexity is also analyzed, and the actual running time of the algorithm can be effectively improved in the final test data performance. It effectively makes up for the shortness of the primary fruit fly algorithm. In addition, in the results and discussion stage, the performance comparison of the Levy flight optimization Drosophila algorithm with the Chaotic Step Optimization Fruit Fly Algorithm (CSFOA) and the Exponentially Decreasing Step Optimization Fruit Fly Algorithm (TEFOA) in terms of average accuracy and standard deviation of the algorithm can be concluded that, in the context of solving the problem of enterprise management, the optimization Drosophila algorithm based on Levy step length has a decisive advantage. In the actual operation and management of enterprises, the rational use of the Drosophila algorithm can effectively solve the problem of resource allocation, but at the same time, the enterprise itself should not be overly dependent on technology; it should also strengthen the training of employees, have more reserves of management and technical personnel, and actively explore new management solutions. From a technical point of view, the optimized Drosophila algorithm based on Levy's flight will increase the time complexity of its algorithm in the face of the large population size and the high number of algorithm iterations. Therefore, new optimization algorithms can be tried in future exploration to solve the problem of algorithm time complexity in large-scale populations.

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