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RESEARCH ON PORTFOLIO INVESTMENT DECISION MODEL BASED ON PARTICLE SWARM HYBRID OPTIMIZATION ALGORITHM

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Abstract: Aiming at the problem that the current portfolio investment decision-making model does not consider the impact of market, investors and other factors on investment decision-making, resulting in low investment return and decision accuracy, a portfolio investment decision-making model based on hybrid particle swarm optimization algorithm is proposed. On the basis of studying the realistic constraints of portfolio investment, the risk and return of portfolio are calculated quantitatively. After selecting the operation strategy of portfolio investment assets, the portfolio investment decision-making model is established, and the hybrid optimization algorithm of particle swarm optimization is used to solve the model. Simulation results show that the proposed method can improve the decision accuracy by at least 12.51%, and can effectively improve the return on investment.

Key words: particle swarm optimization algorithm; Portfolio investment; Investment decision model;

0 Introduction

In recent years, China's social economy has been in a period of high and sustained growth, and the income of residents has been increasing. Although the traditional bank savings have been steadily increasing in the structure of social capital flow, the diversified development of investment methods in the financial market and the change of residents' financial management concepts have prompted more and more residents to adopt financial investment behaviors with higher yields and invest part of their funds in the securities market. Although investing funds in the securities market can obtain higher yields, investment in the securities market has higher risks, and investors generally use portfolio investment to invest. Portfolio investment usually means that investors analyze the investment risks of all investment products, predict the development trend of securities in the corresponding industry, as well as the investment risks and returns, according to certain investment theories. However, it is worth noting that in the process of securities investment, different investors have different investment cost inputs, expected returns, risk expectations, and risk bearing capacity [1]. Therefore, according to the portfolio investment theory, different securities are searched for in a specific period of time, and according to a certain investment ratio, which makes it possible to obtain the maximum investment return under the condition of fixed investment risk, or minimize the investment risk under the condition of the expected return as close as possible. Generally speaking, investment risk is the probability of the difference between the actual level of return and the expected level of return of the invested assets, and is mostly characterized by the risk-return rate. The use of portfolio investment can protect against additional investment risks. In practical investment decisions, choosing an effectively diversified and

efficient portfolio of securities can help investors avoid investment risks to the maximum extent. However, the use of portfolio investment, although effective in avoiding risks in the investment process, but at the same time will also reduce the rate of return on investment. Usually the more the number of investment assets in a portfolio under a fixed total investment, the more the return of the final portfolio will be diluted. Therefore, when investing, investors can analyze and calculate the return and risk of each investment product, combine the market background factors and the interrelationship between the return and risk of different products, and determine the allocation ratio of investment funds, so as to achieve the goal of maximizing the overall return or minimizing the risk of portfolio investment.

The mean-variance model established by Markowitz investigates how to maximize investment return under a given investment risk or minimize investment risk under a certain investment return. This portfolio investment model converts the original qualitative analysis of portfolio investment risk into quantitative analysis, thus facilitating the use of mathematical analysis and other methods for portfolio investment decisions. As time goes on, investment risk measurement tools have been improved and more research results have been achieved on different portfolio investment models. On the basis of these researched portfolio investment models, portfolio investment decisions are accomplished by introducing other algorithms to optimally solve the relevant portfolio investment models [2].

The tracking error-based portfolio investment decision model mentioned in the literature [3] has relatively simple model variables, while the current changes in the securities market are flexible and the model is no longer applicable. A decision model constrained by transaction costs and minimum trading volume is constructed in the literature [4], but this model, when applied to investments in practice, avoids excessive investment risks but also reduces the expected return of portfolio investments. The portfolio investment decision model based on multi-stage investment mentioned in the literature [5] considers the impact on portfolio returns under different stages, but the model requires a large amount of data analysis when investing, and the model's decision-making efficiency is difficult to meet the actual use. With the continuous development of technology, the problem of portfolio investment is quantified and changed from the original qualitative analysis of the development of the securities industry for investment to the establishment of a relevant portfolio investment model by quantitative analysis of the factors affecting the effectiveness of portfolio investment. Then use intelligent optimization algorithm to solve the mathematical model of portfolio investment, and complete the portfolio investment decision according to the result of the algorithm solution. Therefore, it is particularly important to quantify the investment risk and thus develop a portfolio investment decision plan when making portfolio investments.

Particle swarm optimization algorithm is a heuristic global search algorithm based on population intelligence, which achieves the global optimal point in the complex search space through iteration and update of particle swarm. The algorithm is easy to understand, easy to implement, and has strong global search capability, and is widely used in engineering and medicine, but it is rarely used in the field of securities portfolio [6]. The particle swarm hybrid

optimization algorithm, which is optimized by introducing other algorithms, has the advantages of both algorithms and its processing performance is further improved. Based on the above analysis content, in order to improve the correct decision rate of investment decision model and improve the investor's return, this paper will construct a portfolio investment decision model based on particle swarm hybrid optimization algorithm and verify the effectiveness of the model.

1 Research on the construction of portfolio investment decision model based on particle swarm hybrid optimization algorithm

1.1 A study of the realistic constraints on portfolio investment

All portfolio investments need to consider the numerous factors that affect the return and risk to the portfolio in the actual investment market, so as to determine the realistic constraints of the portfolio. Analyzing realistic portfolio investment, this paper proposes the following realistic constraints on portfolio investment [7-9].

(1) Portfolio investment needs to consider the cost constraints arising from various trading operations in the investment process. Classical portfolio theory usually considers how to obtain the maximum expected return on investment or minimize the investment risk under idealized conditions when studying. For example, classical portfolio theory does not take into account the fees and charges incurred in the process of buying and selling securities, changes in returns during the trading period, etc., when calculating the minimization of investment risk or the maximization of expected investment returns. However, this idealized assumption is obviously not in line with the real securities market trading situation. All global securities trading markets have different transaction costs for securities trading, which can be usually divided into three parts: stamp duty, commission, and transfer fees. In the actual operation of securities buying and selling transactions, transaction costs are bound to be incurred, and they are subject to change depending on factors such as the holding period of investment assets, commissions set by different hiring parties, etc. Therefore, the investor's ultimate gain is equal to the gain from the securities at the time of selling minus the transaction costs incurred in trading operations such as selling. Therefore, in the actual securities investment process, most of the investors' trading operations and selection costs will change the portfolio investment strategy. That is, when making portfolio investment decisions, the cost of securities trading operations is taken into account to determine the proportion of securities in the portfolio.

(2) In actual securities market trading, there are minimum trading volume and integer trading constraints. When classical portfolio theory investigates portfolio investment, it assumes that the purchase volume of all securities involved in portfolio investment can be infinitely subdivided under the condition that it is not zero. However, this assumption is not possible in the reality of securities trading. All global securities trading markets require a certain minimum purchase amount for investors, and for the convenience of calculations, statistics and financial operations, the number of purchases is required to be an integer multiple. In other words, each time an investor buys or sells an investment asset must be greater than or equal to the minimum trading volume and the trading volume must be a whole number.

(3) Portfolio investment requires consideration of the investment sector chosen to meet the diversification requirements. Industry diversification investment refers to the securities investors in the selection of different investment assets in the portfolio, the choice of investment assets belonging to different industries for investment, so as to avoid a decline in the earnings of securities in one industry, affecting the overall portfolio investment income. The use of diversification in the form of portfolio investment can maximize the negative returns of falling investment securities can be offset to a certain extent by the positive returns of growing industries, thus achieving the purpose of reducing the risk of the securities portfolio to ensure the stability of investors' returns. So that when the portfolio, an investment asset in the industry development downturn, corresponding to a certain industry earnings may appear to rise, so that the portfolio of different securities investment returns and risks in each other offset, to minimize investor losses, to maintain the investor's investment mindset.

(4) Portfolio investment needs to consider the liquidity risk of the portfolio assets themselves when investing, the constraints on portfolio decisions. The short-term liquidity risk of portfolio assets is usually characterized by the liquidity coverage ratio in finance. The liquidity risk of portfolio investment assets can be very damaging to the entire securities market and the financial industry. Therefore, when making portfolio decisions, portfolio investors must consider not only the short-term financial risks of the securities industry itself, such as the volatility of securities prices, but also the non-financial risks that can affect portfolio investment decisions, which are called background risks. In general, contextual risks are factors that investors cannot adjust to in the short term, such as income risk, asset changes, health risks, etc. These risk factors affect investors' investment decisions by influencing their lives, psychology, and thus their investment decisions.

After studying the realistic constraints of portfolio investment, the relationship between risk and return of portfolio investment assets is measured in conjunction with the above-mentioned research.

1.2 Portfolio risk-return measures

The risk and return of a portfolio investment are important factors in determining an investor's investment decision, and the return on investment of a portfolio investment is usually measured by the expected rate of return. For a given security, the return can be expressed according to the following equation [10-11].

$$R_t = \frac{P_t - P_{t-1} + D_t}{P_{t-1}} \quad (1)$$

In formula (1), P is the price of the security during the Investment trading operation period t; P_{t-1} is the price of the security during the $t-1$ investment trading operation period; D_t represents the income of the securities during the Investment trading operation period t. Within a portfolio investment, the investment return of the overall portfolio is a weighted average of the return on all invested assets. If a certain investment portfolio contains n investment risk assets, the return on assets of each investment risk asset is known, and the return on assets of each investment risk asset

is affected by the volatility of the securities market. Then the overall return rate of the securities portfolio can be calculated as follows [12] :

$$E\left(r_p\right)=\sum_{i=1}^{n} x_i E\left(r_i\right) \quad (2)$$

In formula (2), r_i is the return on assets of the i investment risk asset in the securities portfolio; x_i represents the proportion of the i investment risk asset in the overall securities portfolio.

For portfolio investments, different investment strategies, investment approaches, types of risky assets invested and investor preferences, etc., affect not only the investment returns but also the overall risk of the portfolio. The overall risk of a portfolio is usually expressed in terms of the variance of the portfolio, which is calculated as follows [13-14].

$$\sigma_p^2=\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \operatorname{cov}\left(r_i, r_j\right), i \neq j \quad (3)$$

In formula (3), $\operatorname{cov}\left(r_i, r_j\right)$ is the covariance between returns of two investment risk assets in a security portfolio. The variance of the portfolio shown above is decomposed according to the return correlation coefficients between the different investment risk assets in the portfolio, and the overall risk of the portfolio can be divided into the investment risk brought by the individual investment risk assets and the risk brought by each asset in the portfolio with a return correlation. According to the risk diversification theory of portfolio investment, the variance of the portfolio shown above can be rewritten in the following form by assigning an average weight to all the securities assets in the portfolio.

$$\sigma_p^2=\frac{1}{n}\overline{\sigma^2}+\frac{n-1}{n}\overline{\operatorname{cov}} \quad (4)$$

In formula (4), $\overline{\sigma^2}$ is the mean variance of all securities in the securities portfolio; $\overline{\operatorname{cov}}$ is the average covariance of all securities in a securities portfolio. From the above equation, it is clear that as the number of securities in the portfolio increases, the risk diversification effect can be used to minimize the portfolio investment risk [15]. The specific relationship is as Figure 1..

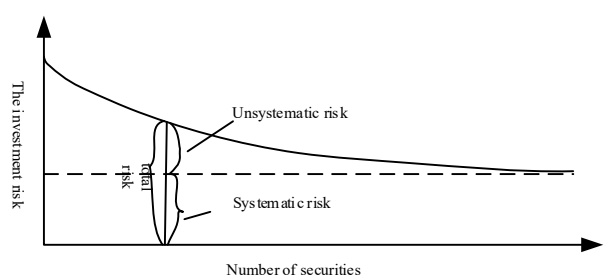

Figure 1 Diagram showing the relationship between portfolio risk and the number of securities in the portfolio

With the fluctuation of the securities market, the yields of different securities fluctuate continuously, and there will be a phenomenon of reducing the overall investment risk of the portfolio due to the offsetting of the investment risks between securities. The greater the correlation

between the returns of securities, the more difficult it is to achieve the effect of mutual offsetting between securities investment risks, therefore, portfolio investment should choose securities with lower correlation between returns for the portfolio.

The relationship between the expected degree of correlation between the returns of each security in the portfolio and the overall investment risk diversification of the portfolio can be summarized in the following cases [16]:

(1) When there is a perfectly positive correlation between the expected returns of each investment security in the portfolio, the portfolio does not generate any risk diversification effect. The smaller the positive correlation between the returns of the securities, the greater the risk diversification effect that can be generated when the portfolio is invested.

(2) When there is a negative correlation between the expected returns of each security in a portfolio, such as a perfect negative correlation, the overall investment risk of the portfolio composed of these securities tends to be close to zero.

Based on the measured portfolio return and risk, the common investment decision strategy for portfolio investment is selected so that the overall portfolio return and investment risk meet the needs of investors.

1.3 Selection of operating strategies for investment assets within the portfolio

When conducting portfolio investment, the selection of investment assets within the portfolio is usually done according to the realistic constraints of portfolio investment mentioned in 1.1. The composition ratio of investment assets within the portfolio and the subsequent investment operation strategy can be divided into three types: benchmark strategy, call strategy, and put strategy. Benchmark strategy mainly refers to an investment strategy in which the investor does not make too much human intervention in the investment process. It can usually be divided into buy-and-hold strategy and fixed ratio strategy. Buy-and-hold strategy means that after investing a certain amount of initial capital into the securities market according to a certain proportion, the proportion of capital invested in each security within the securities portfolio is no longer adjusted according to the operational risk of the market. This investment strategy is an ideal ex-post strategy and is not suitable for making large investments in situations where there is a high volatility in the securities market. The fixed-ratio strategy is to obtain cumulative returns by adjusting the proportion of funds invested in each investment security among different risky assets within the portfolio during each fixed trading cycle. However, this investment method tends to result in higher operational transaction costs. Therefore, the adjustment of investment ratios can only be made at specific trading cycles and this investment operation should not be too frequent [17-18].

The chasing strategy is to increase the proportional weighting of investment in risky assets that perform better in the securities portfolio for each investment trading period in order to obtain higher investment returns. This investment strategy is more risky and can easily cause the investment capital to be trapped. The downside chasing strategy is an investment approach in which the proportional weighting of investments in risky assets in the portfolio that are forecasted to have good future growth trends but perform poorly during the current investment trading period is increased appropriately when investing in the current period. This investment strategy requires

a high level of investment ability from the investor. Usually, in the actual portfolio investment process, the three strategies of benchmark strategy, call strategy, and put strategy are combined with each other to operate the portfolio investment with the premise of minimizing the portfolio investment risk or maximizing the portfolio investment return [19]. After selecting the investment asset operation strategies within the portfolio, a portfolio investment decision model is established and the model is solved using a particle swarm hybrid optimization algorithm.

1.4 Constructing portfolio investment models

Based on the above analysis, the portfolio investment model developed in this paper is shown below [20-21].

$$\begin{aligned} &\max E\left(r_p\right) = X^T R \\ &\min \sigma^2\left(r_p\right) = X^T \sum X \end{aligned} \quad (5) \ .$$

The multi-objective planning model for portfolio investment developed above requires the following constraints to be satisfied.

$$\begin{cases} X^T E_n = 1 \\ L \le X \le U \end{cases} \quad (6)$$

In formula (6), L is the lower limit of securities portfolio investment; U is the upper limit of portfolio investment. Based on the established portfolio investment model established above, a particle swarm hybrid optimization algorithm is used to solve it and complete the portfolio investment decision.

1.5 Particle swarm algorithm improvement optimization

1.5.1 Algorithm adaptation function design

There are more variables to be considered for optimization in the portfolio investment process, which will increase the complexity of the model solution, taking into account that the importance of risk minimization and return maximization for investors varies from person to person. To establish the connection between the objective function of the model and the fitness function: if the objective function plant to be solved is used as the variable of the fitness function, the fitness function can be made positive when the problem to be solved is a maximization problem, and negative when the problem to be solved is a minimization problem. The fitness of each particle is calculated according to the following equation [22].

$$fit\left(x\right) = \frac{1}{1+s-x}, s > 0, s - x > 0 \quad (7)$$

In formula (7), s is the fitness function parameter. The adaptation function corresponding to the particles is obtained by the above calculation, but the particles exist with different superior and inferior traits, and they are distinguished according to the calculated adaptation function. For the inferior particles, we help them to get rid of the inferior position as soon as possible and accelerate the development to other regions; for the superior particles, we strengthen the development of their corresponding regions and dig more excellent solutions. The mean value of particle population

fitness is used to adjust the fitness function. The mean value of population fitness is calculated as follows.

$$fitness\left(x_q\right)=\frac{\sum_{i=1}^{n} f\left(x'\right)_i}{W} \quad (8)$$

In formula (8), W represents the population size, and i is a constant, representing the number of key factors. If the result $fitness\left[x_n\right] > fitness\left(x_q\right)$ is obtained, it indicates that the particle is in an optimal position and close to the optimal solution. Therefore, the search step size of this part of particle is reduced to avoid the step size being too large and missing from the optimal solution. The step size is adjusted by reducing the speed limit imposed by the increase of inertia weight. The formula is as follows [23-24]:

$$fitness\left(x_n\right)=\left(\omega_{\max}-\omega\right)*\frac{fitness\left(x_n\right)}{fitness\left(x_q\right)}*U_{\max}$$
$$U_{\max}=1+\frac{1}{U_0} \quad (9)$$

If $fitness\left[x_n\right] < fitness\left(x_q\right)$, it indicates that the particle is in a inferior position and is far from the optimal solution. By increasing the search step size of the particle, excessive slowness of the search can be avoided. The step size is adjusted by increasing the inertia weight and reducing the speed limit. The formula is as follows:

$$fitness\left(x_n\right)=\left(\omega_{\min}+\omega\right)*\frac{fitness\left(x_n\right)}{fitness\left(x_q\right)}*U_{\max}$$
$$U_{\max}=1-\frac{1}{U_0} \quad (10)$$

In formula (9) and formula (10), ω represents the inertia weight, $\omega_{\min}$ represents the minimum value, $\omega_{\max}$ represents the maximum value, U_0 represents the initial velocity of the particle, and $U_{\max}$ represents the maximum velocity of the particle.

1.5.2 Particle swarm hybrid optimization algorithm for solving decision models

The particle swarm algorithm constantly updates the particle positions and particle velocities when solving, i.e., iteratively updates its own information in the solution space to find the optimal solution to the optimization problem. The flow of hybrid particle swarm optimization algorithm is as Figure 2.

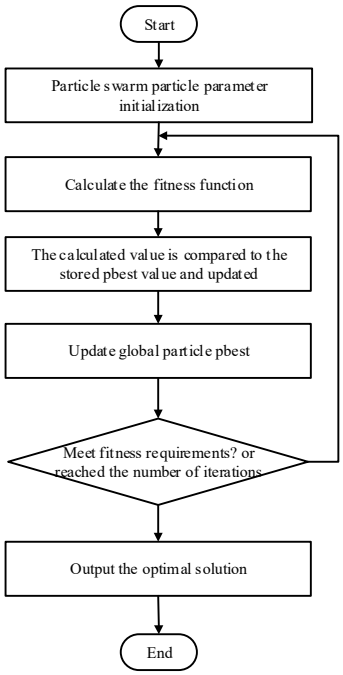

Figure 2 Flow chart of particle swarm hybrid algorithm solution

In Figure 2, in the above figure, the initial velocity and initial position of the particles in the particle swarm hybrid optimization algorithm are randomly selected. Considering each particle as a resource, the optimization process in the swarm of particles relies mainly on inter-population cooperation. At the later stage of the algorithm operation, the presence of a stagnation condition of the particles is calculated by formula (11) [25].

$$\alpha^2 = \sum_{j=1}^{N} \left[\frac{k\left(D_j\right) - \bar{D}}{D} \right]^2 \quad (11)$$

In formula (11), $k\left(D_j\right)$ represents the fitness value of the j th individual, α^2 represents the variance of the fitness of the current population, D represents the normalization factor, and $\bar{D}$ represents the average fitness value of the current population. According to the fitness value of the calculated position variable, the optimal position in the chaotic process is updated.

Considering the global search, in order to deepen the search refinement and ensure the diversity of the overall operation of the particle swarm, a relatively small value of acceleration parameter and a relatively large value of learning factor are selected in the particle swarm algorithm to ensure the forward speed of the particles themselves toward the target. As the number of iterations increases, the velocity and position of the particles are updated in real time using the acceleration and learning factors, and the optimal solution is output at the end of the iteration. During the iteration, the current position of each particle and the calculated fitness value are stored in the pbest of the corresponding particle, respectively. The position and velocity of the optimal particle in the pbest are extracted and the velocity and position of the particle are updated as the parameters of the next iteration of the improved particle swarm algorithm. Compare the new fitness function values, update the information stored in the pbest of the particles until the final global

optimal solution is obtained, and output the corresponding solution result, then the output of the particle swarm hybrid optimization algorithm is the best portfolio investment decision. So far, the construction of the portfolio investment decision model based on the particle swarm hybrid optimization algorithm is completed.

2 Simulation experiment

This paper constructs a portfolio investment decision model based on particle swarm optimization algorithm. In this section, the validity of the model will be verified through simulation experiments.

2.1 Experiment content

The experiment uses the form of using comparative experiments, using the scientific and intuitive nature of comparative experiments, comparing the traditional portfolio investment decision model as a comparison item with the portfolio investment decision model constructed in this paper, and analyzing the comparative differences between the experimental data, so as to verify whether the portfolio investment decision model constructed in this paper is feasible. This experiment uses the investment decision model mentioned in literature [4] and the investment decision model mentioned in literature [5] as the comparison group, and the investment decision model constructed in this paper as the experimental group to complete the simulation example validation.

2.2 Experimental data and environment

In this paper, the historical trading data stored in a securities market in China is selected as the research object, and the trading data of all trading days in this financial securities market from July 1, 2018 to November 12, 2019 is selected from the trading database of the securities market as the test data for the simulation verification experiment.

The experiments were completed on an experimental simulation platform configured with an Intel core i7 CPU with a main frequency of 3.89GHz, 16G of memory and 500G of hard disk storage space. The experimental simulation platform is equipped with professional securities simulation operation software, and the three securities portfolio investment decision models are verified using the professional securities simulation operation software.

2.3 Experimental results

The actual data of three investment decision models are as Table 1. By analyzing the data in the table, the final conclusion of this experiment is obtained.

Table 1 Comparison of experimental test data of three investment decision models

Investment behavior number	Literature [4] model		Literature [5] model		this paper's model	
	Return on investment /%	Decision accuracy /%	Return on investment /%	Decision accuracy /%	Return on investment /%	Decision accuracy /%
1	0.204	62.1	0.456	67	0.913	81.6
2	0.227	57.3	0.372	67.3	0.893	78.6
3	0.182	61.7	0.475	66.4	0.877	81.3
4	0.198	57.8	0.479	68.8	0.892	78.0

5	0.186	59.3	0.486	68.7	0.955	78.1
6	0.196	60.9	0.515	67.9	0.904	81.8
7	0.179	57.6	0.499	66.3	0.883	80.7
8	0.183	60.6	0.399	68.9	0.929	79.9
9	0.22	61.7	0.426	66.5	0.917	78.5
10	0.182	62.6	0.49	67.2	0.958	77.3
11	0.175	59.8	0.494	66.1	0.893	79.4
12	0.185	57.8	0.523	68.4	0.947	78.2
13	0.194	61.5	0.456	66.9	0.956	81.1
14	0.178	60.7	0.391	66.6	0.968	82.6
15	0.173	60.3	0.507	66.3	0.891	79.9

By analyzing the data in Table 1, it can be seen that the investment return rate of the decision-making scheme based on the investment decision-making model mentioned in the two literatures is far lower than that of the decision-making scheme based on the investment decision-making model constructed in this paper. The average investment decision accuracy of the model in reference [4] is 60.11%, the average investment decision accuracy of the model in reference [5] is 67.29%, and the average investment decision accuracy of the model in this paper is 79.8%, which is higher than the other two models. Combined with the data change of the decision accuracy of the model, the practical application effect of this model is better. To sum up, the hybrid particle swarm optimization algorithm can improve the efficiency of portfolio decision-making by at least 12.51%.

3 Conclusion

Securities portfolio is a reasonable combination of all kinds of securities investment in order to avoid the risks of securities investment and ensure the profitability, liquidity and safety of securities investment. Securities investment has a lot of risk factors, investors in order to avoid a single investment in the securities by a kind of absolute risk, usually adopt diversification strategy, the money across to several kinds of securities, and according to the size of the risk, how much profit, flow ability strong and the weak of reasonable combinations, and securities investment risk to the minimum. This paper studies and constructs a portfolio investment decision model based on particle swarm optimization algorithm, and verifies the performance of this model compared with the other two traditional models through experiments.

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