Intelligent Evaluation of Innovative Enterprise Performance - Construction of BPNN Model based on Improved WOA Optimization

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Abstract: -With the economic progress, the environment in which enterprises operation is becoming increasingly complex. Intelligent performance evaluation of innovative enterprises is of great significance for their own development. The traditional performance evaluation indicators of enterprises rely too much on their financial indicators, leading producers and operators to pay more attention to the short-term financial performance growth of the enterprise. The long-term development of enterprises is neglected, resulting in weak core competitiveness. Therefore, to better achieve the scientific evaluation of innovative enterprise performance, based on the innovative enterprise performance evaluation index system, an innovative enterprise performance intelligent evaluation model with the whale optimization algorithm optimized backpropagation neural network is constructed. For the shortcomings of the whale optimization algorithm in the operation, the wolf swarm algorithm isintroduced to optimize it. The experimental results show that the evaluation model based on the improved whale optimization backpropagation neural network proposed in the study has very small errors in the evaluation results of different samples, with no more than 3%. This indicates that the performance evaluation index system for innovative enterprises can objectively reflect enterprise performance. This evaluation model can offer a reasonable analysis of enterprise performance, providing reference for intelligent evaluation of innovative enterprise performance.

Key-Words: -Innovative companies; performance evaluation; improving WOA; BPNN; WPA

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1 Introduction

As the continuous growth of the knowledge economy, enterprises are facing increasingly complex environments and fierce competition. Only by continuously improving their innovation level can enterprises catch up with the growth of the market economy for a long time and not be eliminated by society, [1], [2]. Therefore, innovative enterprises have emerged. Innovative enterprises refer to measures such as enhancing cultural innovation, encouraging communication, clarifying organizational structure responsibilities, and incentive policies to enhance the adaptability of enterprises to flexible markets. By reducing costs and improving product quality, they promote the vigorous development of the social economy. As the foundation and key component of the national innovation system, innovative companies have great impact on globalization. Within the development of innovative enterprises, the scientific evaluation of the economic benefits brought by innovation capabilities is a hot topic for scholars, [3], [4]. The existing performance evaluation of enterprises is mainly based on the enterprise capital turnover and enterprise management. From the perspective of enterprise resource turnover, Protsenko proposed that the financing limit is the main criterion for the sustainable development of each enterprise when evaluating the performance. The financial situation of industrial energy enterprises largely depends on the rationality of the innovation potential structure, [5]. From the perspective of corporate management, [6] found a positive correlation between board size and corporate performance when evaluating corporate performance. The impact of independent director ratio and CEO duality on corporate performance was not significant. Research has shown that optimizing the structure of the board of directors can improve corporate performance. [7] studied the role of corporate social responsibility in driving corporate performance. Green process innovation plays a positive mediating role between corporate social responsibility and corporate performance,. However, unlike traditional enterprise performance evaluation, the evaluation methods of innovative enterprises must adapt to the characteristics of the enterprise and the needs of the times. Therefore, establishing a scientific and innovative function assessment system for companies is of great significance for their own development, as well as for the government and the country. The existing performance evaluation methods for enterprises are applicable to traditional enterprises. Meanwhile, these performance evaluation methods mostly rely on financial indicators to achieve performance evaluation, which cannot objectively reflect the level of enterprise performance. Therefore, to better assess the effectiveness of innovative enterprises, a backpropagation neural network (BPNN) performance evaluation model with the improved Whale Optimization Algorithm (WOA) is constructed on the basis of the designed performance evaluation indicators for innovative enterprises. It is expected to achieve intelligent evaluation of innovative enterprise performance, scientifically layout the resources of innovative enterprises, ensure orderly production and operation, and achieve steady improvement of enterprise performance. The primary structure of the study contains five parts. The first part is introduction. The second part is to analyze the current research on enterprise performance evaluation and BPNN. The third part is to construct an intelligent performance evaluation model for innovative enterprises based on improved WOA-BPNN. The fourth part is to validate the effectiveness of the improved WOA-BPNN intelligent evaluation model. The last part is a summary of the research content.

The specific research contributions are as follows. Firstly, based on the characteristics of innovative enterprises, a performance evaluation index system is constructed that reasonably reflects the performance level of innovative enterprises. Secondly, based on the indicator system, an intelligent evaluation model WOA-BPNN suitable for performance evaluation of innovative enterprises is constructed. Finally, in response to the shortcomings of the intelligent evaluation model in the application process, the Wolf pack algorithm (WPA) algorithm is applied to optimize it. An innovative enterprise performance intelligent evaluation model based on WPA-WOA-BPNN is designed, providing effective support for performance evaluation of such enterprise.

This paper is important for the research of innovative companies. The specific reasons are as follows. Firstly, taking the path of innovative development has been a key method for enterprises to enhance their competitiveness in recent years. As many enterprises gradually implement innovative development strategies, how to measure the innovation level and enterprises development has become an urgent problem to be solved. This study constructs corresponding solutions to this problem. Secondly, based on the performance evaluation methods of ordinary enterprises and the characteristics of innovative enterprises, a more suitable performance evaluation method for innovative enterprises is constructed in the manuscript. It provides direct and effective support for various innovative enterprises to evaluate their own innovation capabilities in the future.

2 Related Works

In terms of enterprise performance evaluation, relatively rich research results have been obtained through long-term research and accumulation, which provide a basis for the performance evaluation of innovative enterprises. [8], designed a scientific and effective assessment index system to assess the performance of international enterprises. The study focused on the influence of financial and structural ratios on performance under the review of the influencing factors of internationalization performance. Adaptive training was accomplished using artificial neural networks. The findings denote that the method is reasonable. In the context of sustainable development, paper companies need to pay more attention to low-carbon strategies. Accordingly, [9], constructed a carbon performance assessment system including carbon input, transfer and output indicators. The indicator weights were determined by hierarchical analysis. The results show that the function assessment system provides a useful reference for enterprises to identify important reasons influencing carbon emissions and carbon performance assessment, [10]. [11], took an innovative leading enterprise as an exampleto establish an evaluation index system from two aspects: innovation capability and enterprise performance. In enterprise innovation ability evaluation, six secondary indicators were selected from three views of innovation input and output and economic benefit to establish the company creative ability assessment index system. In enterprise performance evaluation, 11 secondary indicators were selected from the three perspectives of profitability, operation capability and development capability. Then an enterprise performance evaluation index system was established. The findings indicate that the metric assessment system can evaluate the innovation capability of enterprises,

[12]. [13], used the necessary conditions analysis to explore the influence of six antecedent conditions at the "technology-organization-environment" level on enterprise innovation performance. The study denotes that innovation performance is influenced by several factors. The findings of the study can provide useful insights for enterprises to carry out green innovation practices. [14], used the triple performance approach to construct a effectiveness assessment metric system for corporate green governance. Based on the hierarchical analysis (AHP) and Matlab programming, the weights of each index in the enterprise green management performance evaluation index system were determined.The fuzzy integrated assessment manner was applied to assess the green management effectiveness assessment of industrial enterprises. The findings express that the green management effectiveness assessment metrics system constructed by the "triple performance method" has crucial theoretical significance and utilization value for the evaluation.

The BPNN can be used to learn and train the input sample data to obtain the implicit law of the data samples. According to the law, data prediction is achieved. Liu developed a local utility management performance prediction model according to BPNN model. The local utility management performance was predicted with a sample of 11 regions in the east, middle and west of China. The index system can better achieve the function assessment of local utility management, [15]. [16], analyzed the integration performance statistics of green suppliers based on BPNN. The outcomes denote that it is adoptable to assess the integration effectiveness of green logistics enterprises. With proper calculation methods and models, useful assessment outcomes can be got, which can assess the important aspects of company management and correctly distribute resources. [17], utilized genetic algorithm (GA) to optimize the BPNN method in the evaluation of rivers. GA-BP was developed to determine the weights of these indicators. The water environment index of the river was given the greatest weight, followed by the river hydrology, river aquatic life, river morphology and river social service function indexes. [18], proposed a metal surface defect classification method based on an improved BPNN.The features were extracted from 6 types of fault images such as inclusions, patches, cracks, pitting, rolling and scratches using the local binary pattern (LBP) algorithm. The extracted feature values were used to establish a feature sample library. The BPNN optimized with this method has high accuracy. [19], used BPNN to optimize the DCF model to accomplish the financial data prediction of a company. The research outcomes illustrated that the method can achieve the prediction of the company's financial data, providing data support for corporate investment.

From the above research results, the system of corporate performance evaluation indexes and evaluation methods are abundant. These methods can achieve a relatively reasonable assessment of enterprise performance. However, for the performance evaluation of innovative enterprises, the existing evaluation indexes are not applicable to them, whichcannot accurately evaluate the innovation ability and level of enterprises. Accordingly, depending on the advantages of BPNN in data prediction, the WOA is used to optimize it. Then, an innovative enterprise performance intelligent evaluation method based on WOA optimized BPNN is constructed. It is expected that the evaluation method can better evaluate the creative performance of companies and improve the creativity of innovative enterprises.

3 Construction of an Intelligent Enterprise Performance Evaluation Model based on Improved WOA-BPNN

Innovative companies improve their profit levels and enhance their core competitiveness by continuously innovating their brand concepts, business models, management systems, cultural concepts, and technologies. This chapter constructs an intelligent evaluation model of enterprise performance based on improved WOA-BPNN from the characteristics of innovative enterprises themselves.

3.1 Innovative Enterprise Performance Evaluation Index Construction

Generally speaking, the performance of innovative enterprises is mainly reflected in the economic activities of the enterprise. The organizational structure, departments, and production factors in each industrial chain in the production are associated with the performance of the enterprise. Specifically, every functional department of the company should ensure the close association of performance and establish an effective performance evaluation mechanism. Performance evaluation is a process of continuous development and improvement. In the existing performance evaluation index system, financial indicators occupy a large proportion, which is not suitable to the function assessment of innovative companies, [20].

Table 1. Innovative Enterprise Performance Evaluation Indicator System

Primary indicators	Secondary indicators	Primary indicators	Secondary indicators
Economic benefits	Innovative product sales rate	Social benefit	Energy saving consumption
	Operating revenue growth rate		Elimination of outdated production capacity
	Asset liability ratio		Environmental protection technology investment
	Rate of circulating fund turnover		Financial security
Innovation	Innovation investment capacity		Technical support
	Innovation output capacity		Employment opportunities
	Ability to innovate management systems		Social services
Talent benefits	Employee innovation motivation level	Marketing management	Market share of innovative products
	Employee learning and growth		Ratio of market researchers
	Employee satisfaction level		Sales expenses to operating income ratio

To more accurately analyze the effectiveness of innovative enterprises, taking enterprise M as an example, the performance of this enterpriseare evaluated. In constructing the performance evaluation indexes of this enterprise, the evaluation indexes should be designed strictly according to the principles of operability, scientificity, systematization, simplicity and consensus. Based on the existing information of company performance indicators and the characteristics of innovative enterprises, an innovative enterprise performance evaluation system is established, including five main indicators and related secondary indicators, [21]. The specific index composition is presented in Table 1.

The ultimate purpose of economic behaviour is still to obtain economic benefits. Therefore, financial indicators under the economic return index still have relatively important impact on the above index system. Based on the specific characteristics of innovative enterprises, the innovation ability of enterprises is also used as one of the performance evaluation indexes. In addition, Social benefits are also considered as one of the performance evaluation indicators. The reasons are as follows. Firstly, with the rapid development of the economy, the quality of enterprise development has received more attention. The social benefits created by enterprise development have become an important indicator of the healthy development of the enterprise itself. Secondly, with the rapid development of China's economy, it has become particularly important to pay attention to the quality and prospects of enterprise development. It promotes the healthy and orderly development of the national economy. In addition, the social benefits of enterprises are of great significance for social stability, coordination, and healthy development. Therefore, incorporating social benefits into the evaluation and assessment system can comprehensively reflect the effectiveness of enterprises in terms of social benefits, including environmental protection, social security work, population quality, and quality of life. In addition, talents are the key to enterprise operation, which can directly reflect the overall culture level of the enterprise. Especially for innovative enterprises, talents are the core competitiveness to improve their innovation capabilities. Finally, marketing is also used as one of the performance evaluation indicators of innovative enterprises. Enterprise development not only needs to rely on the functions and attributes of the products themselves, but also needs to continuously develop the sales market. Based on the above evaluation indexes, the index weights are analyzed using the hierarchical analysis method. According to the intrinsic relationship between the indicators, a comparison matrix is constructed as shown in Equation (1).

$$R = (r_{ij})_{mn} \tag{1}$$

In equation (1), r_{ij} is the importance of the element j relative to the element i . R is the reciprocal inverse matrix. Then the indicators are tested for consistency. The indicator weights are determined by the judgment matrix, as shown in Equation (2).

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{2}$$

Based on the judgment matrix R, the feature vector $W = \left[W_1^A, W_2^A, ..., W_n^A\right]$ of R is calculated as the weight of the corresponding second-level index. For the total target weight, it can be calculated by evaluating the weight of the first and the second level indexes, as shown in Equation (3).

$$W = W_1 * W_2 \tag{3}$$

In Equation (3), W indicates the total target weight, i.e., the weight of secondary evaluation indicators in the whole evaluation system. W_1 indicates the indicator weight of each secondary indicator under the target factor dimension. W_2 is the weights of various target factors. The weight coefficients of secondary indicators in the system can be calculated.

3.2 Improving WOA-BPNN Enterprise Performance Intelligence Evaluation Model Construction

In the BPNN model, gradient search technology is used to reduce the error between the actual output and expected output of the network. BPNN mainly contains forward transmission signal and reverse feedback error. When forward transmission is performed, the signal is analyzed and transmitted through the topology of the BPNN. When the output does not match the expected result, the error value is analyzed and fed back to reverse feedback, [22]. In the reverse feedback, the error is reduced by continuously adjusting the weights and thresholds among the neurons in each layer to make the output match the expected value. The computational flow of BPNN is shown in Figure 1 (Appendix).

In the BPNN model, the amount of nodes in the output layer relies on the dimensionality of the target variable in the practical problem.The more commonly used nonlinear transfer function, Equation (4), is used to represent the Hyperbolic functions.

$$f\left(x\right) = \frac{1}{1+e^{x}} \tag{4}$$

In BPNN, the neuron is the most basic unit.The output signal can be expressed as Equation (5).

$$y = f\left(wx+\theta\right) \tag{5}$$

In Equation (5), $f\left(\ \right)$ is a transfer function. y is the output value of the neuron. θ denotes the threshold value. w is the weight coefficient of the network nodes. x is the input signal in the BPNN. A three-layer BPNN structure is used in the research, containing an input, an implicit and an output layer. The input layer receives external data. The input layer generally applies a linear function. The trial-and-error method is used to determine the amount of nodes in the hidden layer, as can be seen in Equation (6).

$$k = \sqrt{m+n} + a, a \in [1,10] \tag{6}$$

In Equation (6), k , m and n are respectively the amount of nodes in the hidden, input and output layers. a is a constant between 1 and 10. In BPNN, the structure concluding a hidden layer can solve any closed interval continuous function. The 3-layer BPNN can be mapped to any dimension, which has the merits of simple structure, simple operation and short running time. Nevertheless, the convergence speed of BPNN is not quick, which has influence on the accuracy of performance assessment results. Therefore, WOA is applied to optimize the BPNN. The WOA mainly solves the optimal solution by simulating whale predation, [23]. The WOA is mainly divided into three phases. The position of any whale in the D space is represented as $X = \left\{x \middle| x_1, x_2, ..., x_D\right\}$. The first is the encirclement phase, where the whale moves to the optimal position when encircling the prey. The whale position is updated as shown in Equation (7).

$$X_i^{t+1} = X_{best}^t - A\left|C * X_{best}^t - X_i^t\right. \tag{7}$$

In Equation (7), X_{best} is the current optimal position. Each dimension of A means a uniformly distributed random number of $\left[-a, a\right]$.The initial value of a takes the value of 2, which gradually decreases to 0 as the amount of iterations increases. C denotes a uniformly distributed random number between $\left[0, 2\right]$. The second stage is the bubble attack. When the whales besiege the prey, they will spew bubbles to narrow the target range and update the position to achieve the local optimum. When the whale is performing bubble attack, the whale position update method is shown in Equation (8).

$$X_i^{t+1} = \left|X_{best}^t - A\right| * e^{bl} * \cos(2\pi l) + X_{best}^t \tag{8}$$

In Equation (8), b is a constant. l presents a random number with a uniform distribution of

$[-1,1]$. The third stage is the search for physical objects stage. At this time, the food location is determined by changing the A vector. When $|A|>1$, the individual whale converges to the reference whale. The position is updated by randomly selecting the reference whale according to the individual, as shown in Equation (9).

$$\begin{cases} D=|C*X_{rand}-X(t)| \\ X(t+1)=X_{rand}-A*D \end{cases} \quad (9)$$

In Equation (9), D denotes the distance between the whale and the prey. C refers to the coefficient vector. X_{rand} is the random reference whale's position vector. Based on the above process, the specific flow of the obtained WOA is shown in Figure 2.

However, the basic WOA has the demerits of low accuracy, slow convergence speed and easy to fall into local optimal solutions when analyzing enterprise performance index data. Therefore, the Wolf pack algorithm (WPA) algorithm is adopted to optimize it. The WPA algorithm is a top-down collaborative search path structure based on artificial wolf (AW) themes and responsibility division, [24]. The social division of labor in the WPA algorithm includes the head wolf, the probe wolf and the fierce wolf. In solving the target data, the wolf activities are classified into 3 smart behaviours, namely wandering, calling and siege behaviours.

In a hunting space, the number of artificial wolves in a wolf pack is N. The number of individuals of the variable to be searched for superiority is M. The state of any AW is denoted by $Q=\{q|q_{a1},q_{a2},...,q_{an}\}$. q_{an} means that the a-th AW is searching for the optimal spatial position in the d space. The target concentration captured by the AW is $Y=f(X)$. Y denotes the solution of the objective function. The distance between any two artificial wolves u and v is shown in Equation (10).

$$L(u,v)=\sum_{i=1}^{D}|x_{ud}-x_{vd}| \quad (10)$$

In the wandering behaviour, the wolf with the best fitness value among the remaining wolves except the head wolf is selected as the probe wolf to search for the optimal solution. After advancing along the direction of $p(p=1,2,...,h)$, the position of the probe wolf i in the d dimensional space is shown in Equation (11).

$$x_{id}^{p}=x_{id}+\sin(2\pi\times p/h)\times step_a^d \quad (11)$$

In Equation (11), a is the probe wolf scaling factor. The step length of the probe wolf forward in the direction of h is $step_a^d$. x_{id} is the initial position where the probe wolf is located. The WPA algorithm takes the optimal solution as the head wolf when it is updated. After each iteration calculation, the obtained value is bigger than the previous value. Then the previous generation of head wolves is replaced with the new head wolf. This method iterates continuously until the optimal solution is obtained. The implementation flow of the WPA algorithm is shown in Figure 3.

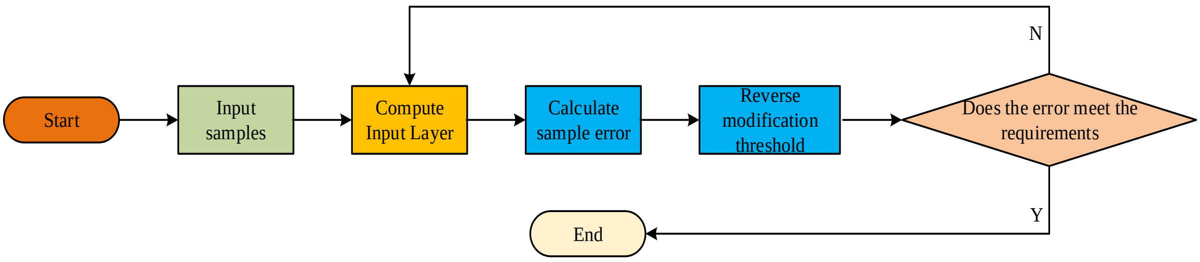

Fig. 1: The structure of BPNN

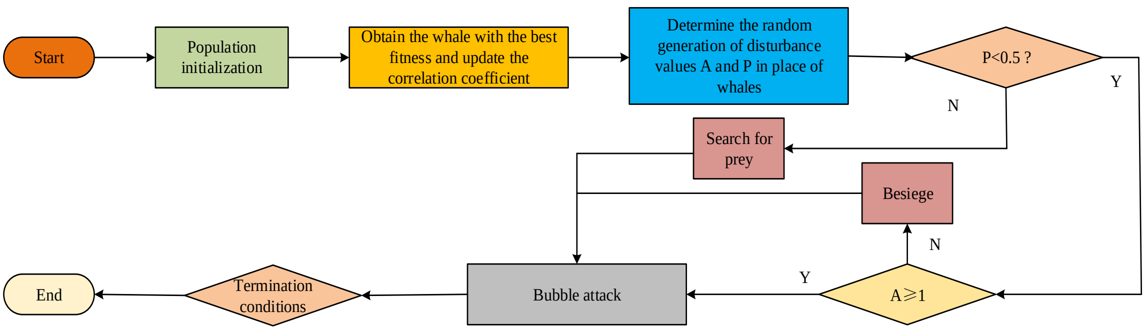

Fig. 2: WOA algorithm process

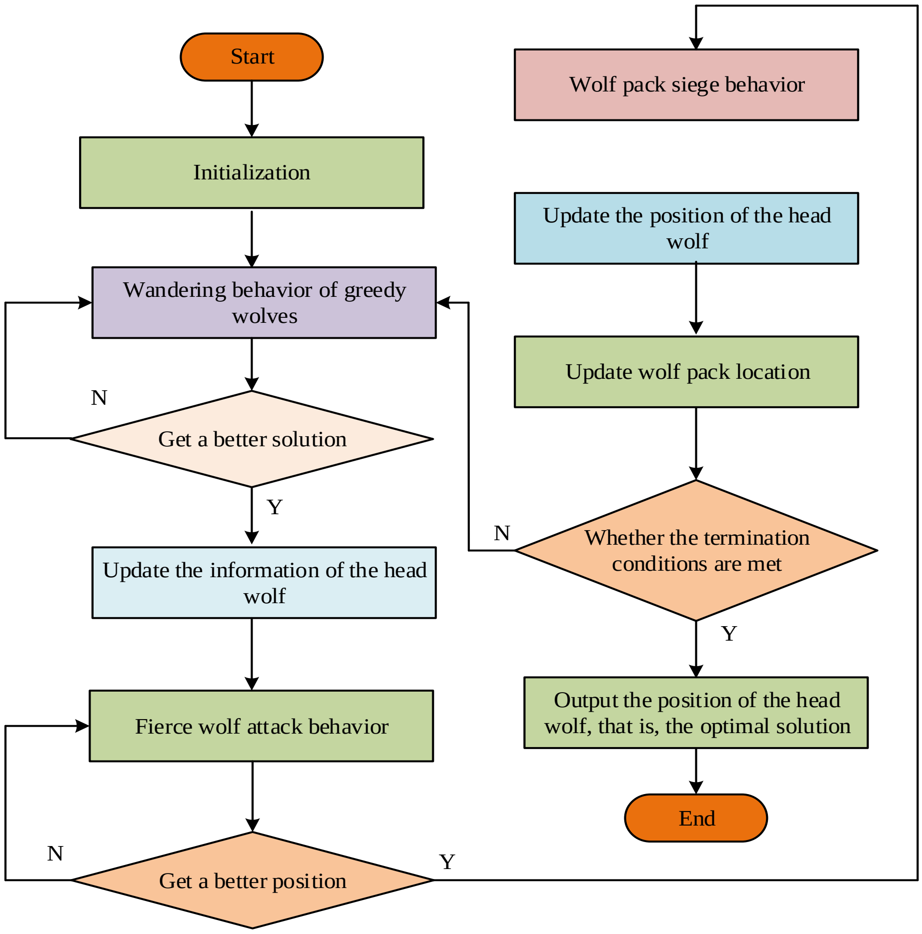

Fig. 3: WPA algorithm process

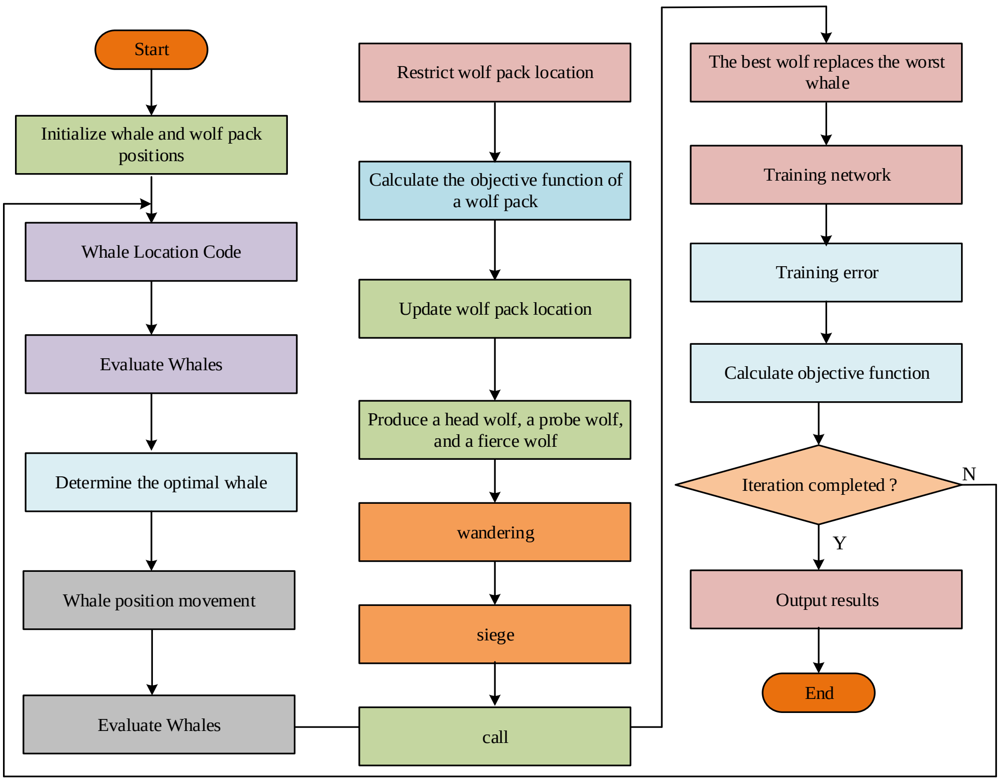

Fig. 4: WOA-WPA-BPNN process

Based on the WPA algorithm, the WOA optimization method is constructed. Depending on the function assessment index system of the innovative company constructed in the above research, the constructed indicators are used as input layer nodes. The output value is the performance evaluation result of this innovative company. The initial values of the BPNN are optimized by improving the WOA algorithm through WPA. That is, the optimal value of WPA is used to replace the worst value of WOA. The optimal value of the output replaces the initial weights and thresholds of the BPNN. The flow of the innovative enterprise performance assessment model based on WOA-WPA-BPNN is shown in Figure 4.

4 Performance Analysis based on the Improved WOA-BPNN Model

To investigate the performance of the improved WOA-BPNN innovative enterprise performance evaluation model, this chapter will test the improved performance evaluation model and the original model. Data related to innovative enterprises are selected to evaluate the performance of the improved model.

4.1 Analysis of Enterprise Performance Evaluation Indicators

Based on the innovative enterprise performance evaluation index system constructed by the research, a corresponding questionnaire is developed and the relevant professionals are invited to rate it. The questionnaire is based on a percentage system. After the evaluation is completed, the valid questionnaires are reasonably collected to obtain the experimental data. According to the analysis method mentioned in the above section, the weights of the performance evaluation indexes for innovative enterprises are finally obtained, as denoted in Table 2. From the relevant weight values, the highest weight of 0.08 is given to the asset-liability ratio, which is the key indicator for the performance evaluation. In addition, the growth rate of business income and innovation management system also has a weight of 0.07. Therefore, to improve the economic efficiency and innovation ability of innovative enterprises, enterprise managers must focus on the enterprise innovation.

Table 2. Evaluation Index Weights

Primary indicators	Secondary indicators	Weight value	Primary indicators	Secondary indicators	Weight value
Economic benefits	Innovative product sales rate	0.05	Social benefit	Energy saving consumption	0.06
	Operating revenue growth rate	0.07		Elimination of outdated production capacity	0.06
	Asset liability ratio	0.08		Environmental protection technology investment	0.05
	Rate of circulating fund turnover	0.05		Financial security	0.05
Innovation	Innovation investment capacity	0.06		Technical support	0.05
	Innovation output capacity	0.06		Employment opportunities	0.04
	Ability to innovate management systems	0.07		Social services	0.06
Talent benefits	Employee innovation motivation level	0.05	Marketing management	Market share of innovative products	0.05
	Employee learning and growth	0.05		Ratio of market researchers	0.06
	Employee satisfaction level	0.04		Sales expenses to operating income ratio	0.06

4.2 Effect Analysis of the Improved WOA-BPNN Performance Evaluation Model

The improved intelligent performance evaluation model based on WOA-BPNN was comprehensively and scientifically analyzed by constructing an innovative enterprise performance evaluation indicator system and calculating indicator weights. In Matlab2013b, the improved WOA-BPNN innovative enterprise performance evaluation model is simulated. The error threshold of the BPNN is 0 and the learning rate is 0.01. The training results of the BPNN model are illustrated in Figure 5. From Figure 5(a), the mean square error of WOA-BP decreases more rapidly in the first 28 iterations, slows down in the 29th to 81st iterations, and reaches convergence after 85 iterations. From Figure 5(b), the WPA-WOA-BP is fast in the first 2 iterations, slows down in the 3rd to 8th iterations, and reaches convergence in the 19th iteration. It raises the convergence speed of the BPNN to some extent. In Figure 6, the convergence speed of WPA-WOA-BP is increased by 79.41% and the convergence accuracy is nearly doubled. The results confirmed that WPA has good optimization effects. WPA-WOA-BP can not only accelerate the convergence speed, but also improve the convergence accuracy to a certain extent.

To verify the convergence of the WPA-WOA-BP, several methods are run in three different functions to calculate the effectiveness of the method. The WSOA, IWOA algorithm and PSO algorithm are used as comparative method. The research findings of the WOA and the improved WOA in the multi-peaked function are shown in Figure 6. From Figure 6, the WPA-WOA method requires the smallest number of iterations in all three different functions, which are 40, 100 and 90, respectively. From this data, the efficiency and speed of the algorithm are significantly higher than other comparison methods. That is, this method is significantly superior to other optimization methods.

The comparison of the fitness values between the WOA-BP and WPA-WOA-BP is displayed in Figure 7. In Figure 7(a), the average and best fitness converge rapidly until the 18th generation, slow down from 30 to 60 generations, and level off after 65 iterations, with the fitness value stabilizing at 0.82. In Figure 7(b), the WPA-WOA-BP fitness converges at the 19th. The fitness value stabilizes at 1.33. From the comparative analysis in Figure 7, the improved model has strong adaptability and faster convergence speed. The optimal and average fitness values of the improved method are better than those of WOA-BP, indicating that the method has strong problem-solving ability in the optimization process.

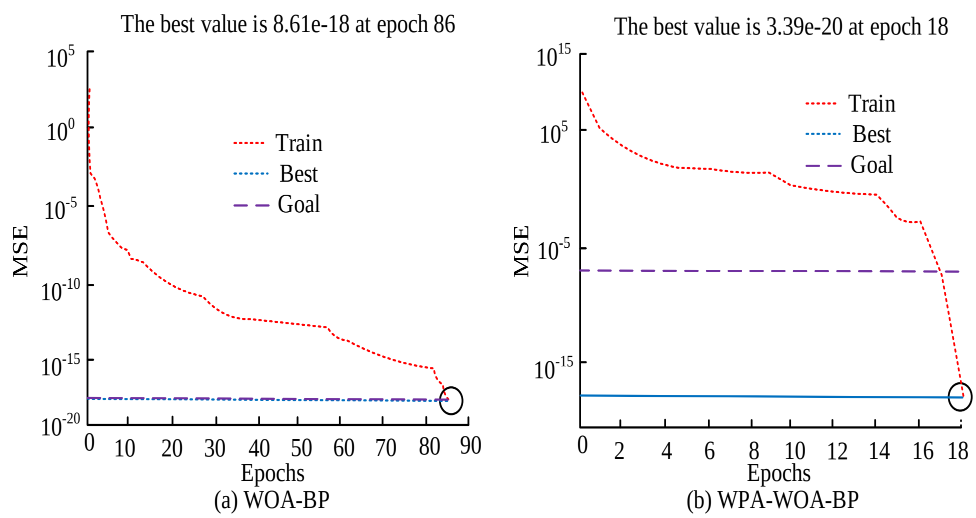

Fig. 5: Mean square error of BP under two algorithms

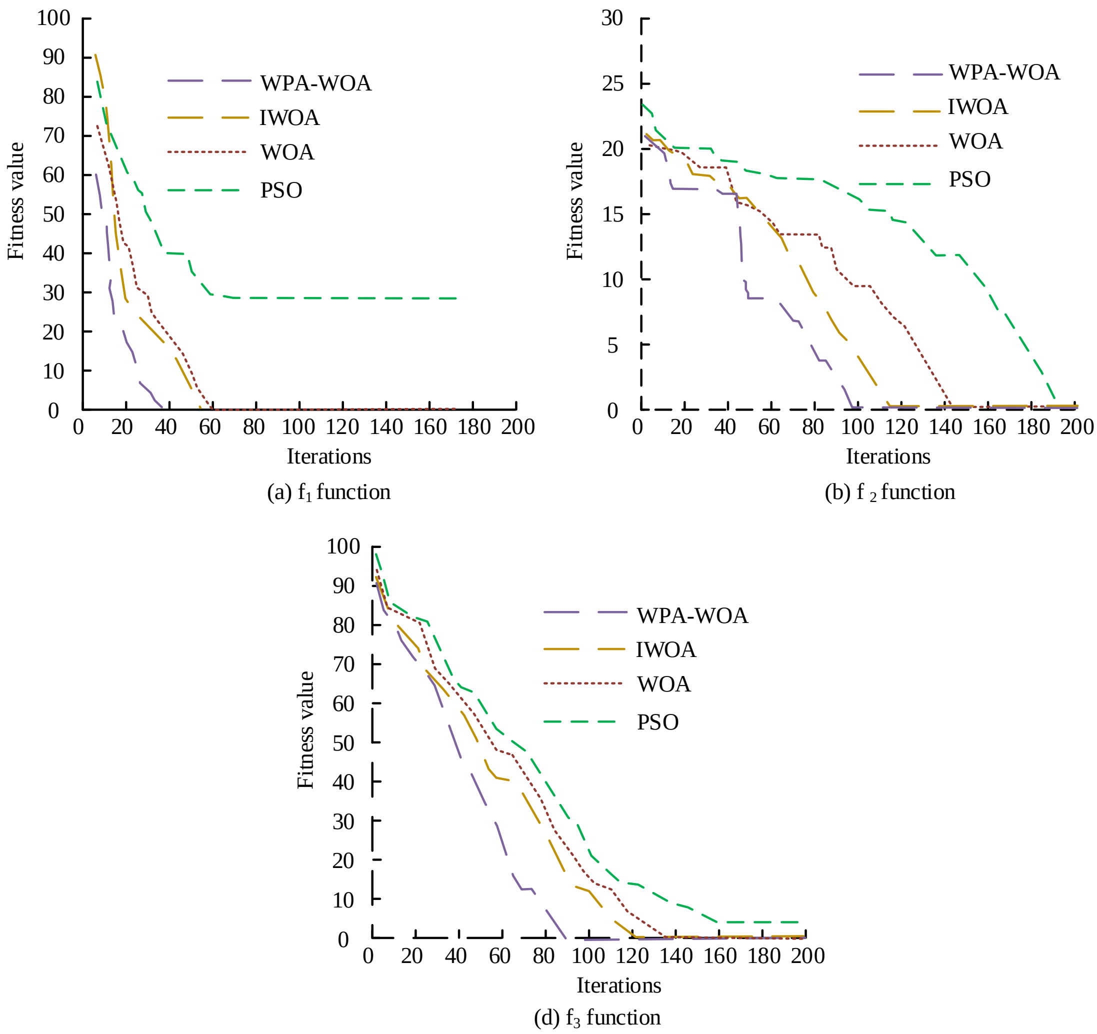

Fig. 6: Comparison of Convergence in Different Functions

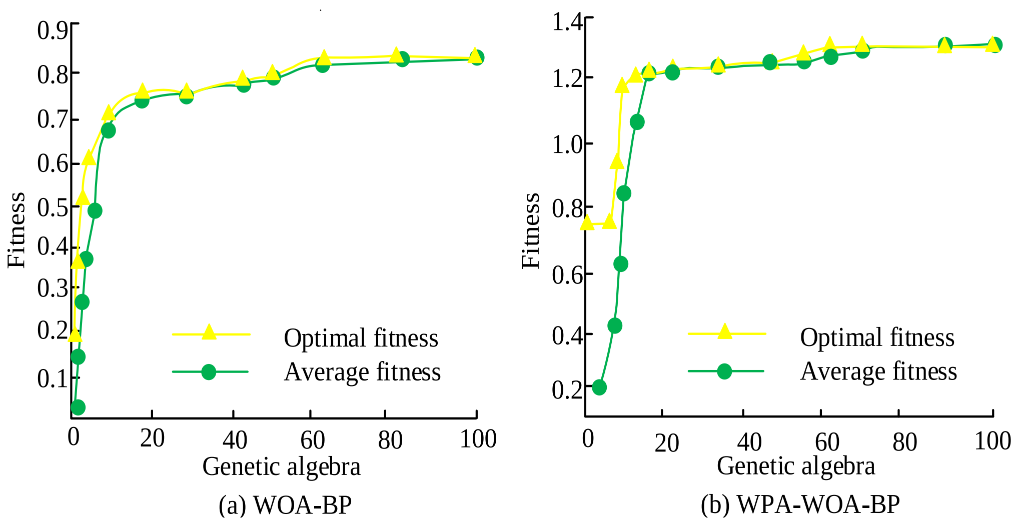

Fig. 7: BP fitness in the two algorithms

Table 3. Performance Comparison of Models

Algorithm	R^2	MSE	RMSE	MPAE	MAE
WPA-WOA-BP	0.9649	0.0177	0.0213	1.1460	0.0091
WOA-BP	0.9653	0.1546	0.0674	3.5097	0.0422
BP	0.8867	1.0643	0.1906	6.4508	0.0766

The R2 values, MSE, RMSE, MPAE, and MAE values of this intelligent evaluation algorithm are compared separately. The nearer the value of R^2 is to 1, the better the performance of the model. The performance comparison of this performance evaluation method is shown in Table 3. From Table 3, the MSE, RMSE, MPAE and MAE of WPA-WOA-BP are 0.0177, 0.0213, 1.1460 and 0.0091, respectively, which is significantly lower than the remaining methods. Different error evaluation indicators are used to measure the performance of the constructed methods, resulting in relatively low error levels. The error level of the performance evaluation method for innovative enterprises constructed through research is relatively low. It can be applied to evaluate the performance of innovative enterprises.

To verify the consistency and stability of the innovative enterprise performance intelligence evaluation method proposed by the research, 20 companies are selected for testing. 10 samples are utilized to train the network and the other 10 samples are evaluated. The optimized BPNN and traditional BPNN models are applied to the same dataset for training and testing. The obtained evaluation results with expected values are shown in Figure 8. From Figure 8, the basic change trends of the performance evaluation results for innovative enterprises obtained under the three different performance evaluation methods are consistent. Specifically, the differences between the effectiveness assessment manners based on BPNNs and the expected values are significant. Among them, the differences between data sample 1, data sample 4 and data sample 6 and the expected performance are the largest. The differences between the performance evaluation results obtained based on the WOA-BP and the expected performance are also relatively significant, with large deviations in samples 2, 4, and 5. The difference between the results obtained by the WPA-WOA-BP performance evaluation model and the expected performance is the smallest, and the fit between the two is the highest. The evaluation is relatively stable for each sample. When the enterprise performance evaluation method is applied to actual enterprise performance evaluation, it can better reflect the innovation and development situation of the enterprise. The intelligent performance evaluation method proposed in the research has good performance evaluation results for innovative enterprises.

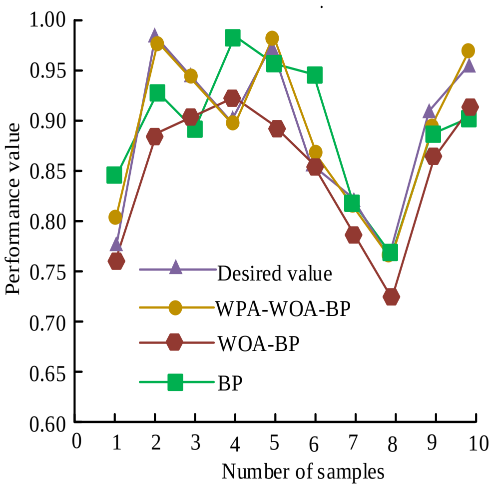

Fig. 8: Comparison of evaluation performance and expected performance

The evaluation results of the performance for 10 different innovative companies based on the improved WPA-WOA-BPNN are expressed in Table 4. From the above evaluation results, the performance evaluation ranking of innovative companies obtained from the training and testing results has not changed. It indicates that the improved WPA-WOA-BPNN model for intelligent performance evaluation has better stability. In the tests of different samples, the errors of the evaluation results are very small. All results do not exceed 3%, which indicates that the intelligent evaluation method has relatively ideal accuracy. The constructed innovative enterprise performance intelligent evaluation method can accurately reflect the innovation ability the enterprise, while measuring the shortcomings of the enterprise in the innovation development.

Table 4. Performance evaluation of different companies

Order number	Evaluate results	Actual results	Error
1	0.8633	0.8621	0.140%
2	0.7564	0.7412	2.010%
3	0.6135	0.6086	0.799%
4	0.8795	0.8822	0.307%
5	0.5536	0.5671	2.439%
6	0.7623	0.7502	1.587%
7	0.8921	0.8882	0.437%
8	0.5406	0.5319	1.609%
9	0.4789	0.4852	1.317%
10	0.6573	0.6625	0.791%

5 Conclusion

By analyzing the existing enterprise performance evaluation indexes, a performance assessment metrics system for innovative companies is constructed. By calculating the index weights, an optimized BPNN intelligent evaluation model with the improved WOA is designed to assess the innovative enterprises performance. The research outcomes demonstrated that among the index systems constructed by the research, the weight value of the asset-liability ratio index is 0.08, which has the greatest influence on the performance level of innovative enterprises. The WPA-WOA-BP fitness reaches convergence at the 19th. It stabilizes at 1.33. The MSE, RMSE, MPAE and MAE of WPA-WOA-BP are 0.0177, 0.0213, 1.1460 and 0.0091, which are significantly lower than the rest of the methods. The performance evaluation index system for innovative enterprises constructed through research can better reflect the influencing factors of the performance. The performance intelligent evaluation model constructed based on this indicator system exhibits higher convergence effects and lower error value performance. The accuracy obtained by applying the proposed method to the performance evaluation for innovative enterprises is superior to other commonly used methods. In summary, this indicates that the proposed intelligent performance evaluation method for innovative enterprises based on improved WOA-BPNN has better performance, which can be utilized the performance assessment of innovative enterprises. However, there are still shortcomings in the manuscript. First, when constructing the performance assessment indicators system of innovative enterprises, the influencing factors analysis is not comprehensive enough. The performance influencing indexes may be different for different types of innovative enterprises. Secondly, there is no professional standard for selecting the structure of BPNN in the manuscript. The optimal structure is verified through multiple experiments, which may have some errors. Additionally, the number of test samples selected for the intelligent evaluation of the performance for innovative enterprises is limited. Therefore, in the subsequent research, a more integrated analysis of the performance assessment indicators for innovative enterprises should be conducted to ensure full coverage of the indicators. At the same time, more sample data should be collected to verify the performance of the model.

References:

[1] Zhang Y. Application of improved BP neural network based on e-commerce supply chain network data in the forecast of aquatic product export volume. Cognitive Systems Research, 2019, 57(10): 228-235.
[2] Yu C, Wang T, Gu X.Collective reputation cognition,network competence and enterprise innovation performance.Management decision, 2022,60(3):567-588.
[3] Walls A J. Design- Led Innovation: A Framework for the Design of Enterprise Innovation Systems.Design Management Journal, 2021, 16(1):93-110.
[4] Xu C, Zhu D.Sustainable Development of Pharmaceutical Industry: Balancing Enterprise Innovation with Public Interests.International Journal of Sustainable Development and Planning, 2020, 15(5):639-645.
[5] Protsenko A V. Conceptual bases for managing the structural transformations of the innovative potential of industrial energy enterprises. Business Inform, 2020, 1(504): 91-99.
[6] Yang L, Chen Y. The empirical study of board structure and firm performance-innovative small enterprises in China. Management Studies, 2021, 9(3): 226-233.
[7] Achi A, Adeola O, Achi F C.CSR and green process innovation as antecedents of micro, small, and medium enterprise performance: Moderating role of perceived environmental volatility.Journal of Business Research, 2022, 139(2):771-781.
[8] Bhatnagar V, Majhi R. Development and comparative performance evaluation of neural network classification techniques for manufacturing sector firms on the basis of new product growth rate. International Journal of

Business Information Systems, 2020, 33(2): 157-179.
[9] Jain K, Saxena A. Simulation on supplier side bidding strategy at day-ahead electricity market using ant lion optimizer. Journal of Computational and Cognitive Engineering, 2023, 2(1): 17-27.
[10] Yang G, Zhou X, Liang Z. Enterprise internationalization performance evaluation model based on artificial neural network. International Journal of Embedded Systems, 2020, 13(4): 387-397.
[11] Zhang C P, Yue W J, Tan D M, Su Z K. Carbon performance evaluation system and practice analysis for the sustainable enterprises. Sustainable Development, 2022, 31(1): 292-306.
[12] Haar J, O'Kane C, Daellenbach U. High performance work systems and innovation in New Zealand SMEs: Testing firm size and competitive environment effects. The International Journal of Human Resource Management, 2022, 33(16): 3324-3352.
[13] Mao K, Tian Y. Influence of increased shares on the performance of liquor listed companies: A factor-based analysis. Ecological Economy, 2020, 16(2): 90-101.
[14] Zhou J T, Wang H B. Assessing green management performance of industrial enterprise: A case study of BH Petrochemical Co. Ltd at the high-efficiency ecological economic zone of the Yellow River Delta. Ecological Economy, 2020, 16(1): 60-69.
[15] Liu X. Forecasting utilities management performance based on discriminant technology and BP neural network. Journal of Intelligent and Fuzzy Systems: Applications in Engineering and Technology, 2021, 40(2): 3207-3214.
[16] Wang Y, Fu P. Integration performance statistics of green suppliers based on fuzzy mathematics and BP neural network. Journal of Intelligent and Fuzzy Systems, 2021, 40(2): 2083-2094.
[17] Hu W, Li W M, Wang L, Su Y F, Sun X, Li J J, Chen Q. Health assessment of small and medium rivers based on GA-BP optimization model. Acta Ecologica Sinica, 2021, 41(5): 1786-1797.
[18] Yue X, Ma G, Liu F, Gao X L. Research on image classification method of strip steel surface defects based on improved Bat algorithm optimized BP neural network. Journal of Intelligent and Fuzzy Systems: Applications in Engineering and Technology, 2021, 41(1): 1509-1521.
[19] Xu L P, Huang F M, Wu F H, Fan R Q. Grade evaluation of black-odorous urban rivers in the Greater Bay Area of China using an improved back propagation (BP) neural network. Environmental Science and Pollution Research International, 2023, 30(19): 55171-55186.
[20] Niu Y, Zhou Y Q, Luo Q. Optimize star sensor calibration based on integrated modeling with hybrid WOA-LM algorithm. Journal of Intelligent and Fuzzy Systems, 2020, 38(2): 2693-2691.
[21] Yang Y, Song X. Research on face intelligent perception technology integrating deep learning under different illumination intensities. Journal of Computational and Cognitive Engineering, 2022, 1(1): 32-36.
[22] Cai B, Sun X, Wang J, Yang C, Wang Z D, Kong X D, Liu Z K, Liu Y H. Fault detection and diagnostic method of diesel engine by combining rule-based algorithm and BNs/BPNNs. Journal of Manufacturing Systems, 2020, 57(7): 148-157.
[23] Zhao Q, Liao W, Wang S, Pillai J R. Robust voltage control considering uncertainties of renewable energies and loads via improved generative adversarial network. Journal of Modern Power Systems and Clean Energy, 2020, 8(6): 1104-1114.
[24] Choi J H, Kim K M, Kwak J W. WPA: Write pattern aware hybrid disk buffer management for improving lifespan of NAND flash memory. IEEE Transactions on Consumer Electronics, 2020, 66(2): 193-202.

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