The GSO-Deep Learning-based Financial Risk Management System for Rural Economic Development Organization

Weiliang Chen
Shanghai Open University Jingan Branch; Shanghai Jingan District College, Shanghai, China

***Abstract*—Financial risk management has always been a key concern for major enterprises. At the same time, with the continuous attention to impoverished rural areas worldwide, financial risk management tools have become an important component of rural economic development organizations to avoid financial risks. With the rapid development of artificial intelligence technologies such as neural networks and deep learning, and due to their strong learning ability, high adaptability, and good portability, some financial risk management tools are gradually adopting technologies such as neural networks and machine learning. However, existing financial risk management tools based on neural networks are mostly developed for large enterprises such as banks or power grid companies, and cannot guarantee their full applicability to rural economic development organizations. Therefore, this study focuses on the financial risk management system used for rural economic development organizations. In order to improve the accuracy of deep learning algorithms in predicting financial risks, this paper designs an improved Glowworm Swarm Optimization (IGSO) algorithm to optimize Deep Neural Networks (DNN). Finally, the effectiveness of the financial risk management tool based on IGSO-DNN proposed in this article was fully validated using data from 45 rural economic development organizations as a test set.**

Keywords—Deep learning; Glowworm Swarm Optimization (GSO) algorithm; Deep Neural Networks (DNN); financial risk prediction; rural economic development organization

I. INTRODUCTION

Financial risk management aims to reduce the probability of adverse risks and mitigate their impact on the enterprise, in order to maintain the financial health and sustainable development of the enterprise. It is an important means to reduce the adverse effects of the enterprise's financial condition and operating performance, and protect the financial interests of the enterprise [1]. Financial risk prediction provides the main data and information for financial risk management, thereby providing the decision-making basis and foundation for financial risk management for enterprises. Specifically, financial risk prediction can be based on historical data, market trends, industry analysis, macroeconomic and other indicators to predict potential financial risk events and their potential impacts [2]. Financial risk prediction helps enterprises identify and evaluate risks in advance, develop corresponding risk management strategies and measures, and reduce the adverse impact of financial risks on the enterprise. It can be said that financial risk prediction is an important component of financial risk management [3].

The financial ratio analysis method evaluates the financial condition of a company by calculating financial indicators such as debt ratio and current ratio. The trend analysis method predicts the future financial condition of a company by observing historical trends in data, and the financial model risk prediction method based on statistical and empirical methods are three traditional financial risk prediction methods, which have high universality and advantages. However, the above three methods also have drawbacks such as low prediction accuracy, susceptibility to limitations in predictions from different industries, and high dependence on data reliability. For example, early risk management systems based on option pricing models had high universality, but their risk prediction performance was not very ideal [1]. Therefore, in early research related to financial risk management, the purpose of a large amount of research was to develop financial risk management tools that can effectively communicate with organizations in the market, rather than improving the accuracy of financial risk prediction models and the reliability of results.

With the advancement of relevant technologies in the field of artificial intelligence, financial risk prediction methods based on cutting-edge technologies such as neural networks, snake venom learning, and machine learning in the field of artificial intelligence are receiving widespread attention from relevant researchers. Learning based financial risk prediction methods can better handle large amounts of data, nonlinear relationships, and complex risk factors, and are expected to bring higher accuracy and reliability to financial risk prediction [3]. Indicative examples include risk management for large financial enterprise investment portfolios based on deep learning [4], enterprise financial risk prediction methods based on genetic algorithms and Support Vector Machines (SVM) [5], and power company financial risk prediction methods based on machine learning [6].

When using machine learning and other methods for financial risk prediction, the first step is to prepare a financial dataset for prediction, including financial statements, economic indicators, etc. At the same time, it is necessary to preprocess the data, including steps such as data cleaning, feature selection, and standardization. Furthermore, it is necessary to select appropriate features from financial data based on the objectives of financial forecasting. Common features include profit, sales, cash flow, etc. Finally, the prediction model is trained and evaluated. In addition, some studies will also further optimize the model, such as selecting genetic algorithms for SVM optimization in study [5].

However, in recent years, rural counties in the United States have replaced large cities as the most difficult areas, and this situation is similar in most parts of the world [7]. With the proposal of the United Nations Sustainable Development Goals, the global attention to economically disadvantaged rural areas is also constantly increasing. This has led to increased funding for difficult rural areas by rural economic development organizations, including the World Bank's rural development department, the Agricultural Development Bank (ADB), the International Fund for Agricultural Development (IFAD), La Via Campesina, and the Rural Development Foundation [7]. These agricultural economic development organizations usually collaborate with local-residents to provide assistance to the impoverished population in the form of rural cooperatives [8].

In order to ensure the sustainable development of rural economic development organizations, rural economic development organizations need to use financial risk management tools to protect their agricultural assets and improve the financial health of rural economic development organizations, in order to attract investment for rural economic development organizations and ultimately achieve sustainable development of rural economic development organizations, maintain agricultural production and stability of rural economy [9]. Therefore, it is necessary to develop corresponding financial risk prediction tools for rural economic development organizations. However, as previously mentioned, existing risk prediction systems based on artificial intelligence methods are mostly used for power, finance, and investment enterprises, rather than agricultural enterprises with agricultural economic development organizations as the main body.

Therefore, this study focuses on the study of a financial risk prediction system for rural economic development organizations, aiming to help them protect organizational assets, improve financial health, increase investment attractiveness, and promote sustainable development of the organization. The main contributions of this article are summarized as follows: Firstly, based on the possible risk sources of rural economic development organizations and the Analytic Hierarchy Process, a deterministic financial risk system was established, aiming to predict financial risks based on the current operating conditions of the company. Furthermore, a novel deep learning prediction algorithm was designed to optimize the Deep Neural Network (DNN) using the improved Glowworm Swarm Optimization (GSO) algorithm, thereby designing the optimal number of DNN layers and parameters, and improving prediction accuracy. Finally, this article used 110 test sets and 45 test sets, and compared the IGSO-DNN algorithm designed in this article with the other two algorithms to verify the effectiveness of the algorithm designed in this article.

The rest of this article is arranged as follows, and the work related to this study is reviewed in the Section II. In Section III, A financial risk prediction model has been established. The Section IV introduces the GSO algorithm. In Section V, the improved GSO algorithm was designed and a model of DNN based on the improved GSO algorithm was developed. The Section VI presents and discusses the simulation experimental results. Finally, the full text is summarized in Section VII.

II. Related Works

This article aims to establish a financial risk prediction tool for rural economic development organizations and use the improved GSO-based DNN algorithm (IGSO-DNN). Therefore, this article reviews the relevant work from three perspectives: financial risk prediction, swarm intelligence algorithms, and machine learning algorithms.

A. Financial Risk Prediction

As previously mentioned, traditional financial risk prediction models have drawbacks such as low accuracy and high requirements for data accuracy [1]. Therefore, this article focuses on financial risk prediction methods based on logistic regression, decision trees, random forests, SVM, and neural networks. In order to enrich the financial risk prediction system based on SVM, works [5], [10]-[11] all used Support Vector Machines (SVM) to predict the financial risk of enterprises. Unlike the simple improvement of SVM algorithm in [10]-[11], work [5] optimizes SVM algorithm based on genetic algorithm (GA), aiming to improve the prediction accuracy of SVM algorithm. The above three studies are based on the actual operational situation of the company, and predict the financial risk of the company based on information such as the intensity of capital investment, capital loss rate, and product net profit. However, Tsai et al. used information from the company's financial reports to predict the company's financial risks [12].

Unlike the above efforts to improve the accuracy of financial forecasts, the work [13] aims to reduce the cost of misclassification. Chen et al. used a Markov chain based Monte Carlo method to predict the financial risks of enterprises before and after economic crises. This study helps companies avoid financial risks caused by economic crises. Reference [14] studies the impact of intelligence services on sustainable financial risk management of enterprises from the perspective of green finance. Yang et al. aim to improve the financial management capabilities of enterprises and provide sustainable financial management plans for them [15]. Specifically, Yang et al. used deep learning methods to predict the degree of financial risk in enterprises and developed a financial risk prediction framework based on DNN [16]. This study explores the application of DNN in financial risk prediction. Reference [17] conducted research on enterprise financial risk prediction models based on BP neural networks, further proving the superiority of AI based financial risk prediction models compared to traditional methods.

Similar to study [14], research in [18] also studied the financial risk prediction of enterprises based on the Markov chain Monte Carlo method, which mainly focuses on the financial market and has certain significance for the development of the financial market. The study in [19] is also based on deep learning to evaluate credit risk, which is also a model for financial risk assessment. The research in [20] studied a credit risk prediction model based on graph neural networks, which evaluates and predicts credit risk based on high-dimensional data and different economic cycles. The above two studies on credit risk prediction have certain reference significance for financial risk prediction. Peng et al. conducted research on several mainstream financial risk prediction methods to evaluate the effectiveness of nine financial prediction algorithms [21].

B. Swarm Intelligence Algorithm

Similar to study [5], this article uses swarm intelligence algorithms to optimize DNN, aiming to improve its performance. At present, with the increasing frequency of large-scale complex problems, swarm intelligence algorithms are also widely studied [22].

The GSO algorithm, as a relatively novel swarm intelligence algorithm, has been widely used in optimization problems since its inception. Reference [22] provides a detailed introduction to the basic principle, process, and parameter settings of the GSO algorithm, and verifies its performance through experiments on multimodal optimization problems. The research in [23] elaborates on the principle and application of GSO algorithm, and provides new ideas for improving and expanding GSO algorithm. The study in [24] mixed the GSO algorithm with another swarm intelligence algorithm and conducted experiments on complex global optimization problems. The experimental results show that the hybrid GSO algorithm has higher accuracy and convergence speed in global optimization compared to traditional GSO swarm algorithms. The study in [25] provides a detailed introduction to the application of GSO algorithm in the field of intelligent manufacturing, and prospects its applications in power system scheduling, network routing, resource allocation, image processing, and other fields.

Particle Swarm Optimization (PSO) algorithm, as a heuristic algorithm, is widely used in fields such as robot path planning, image recognition, vehicle scheduling, and flight planning [26]. The research in [27] introduces improvement strategies for the PSO algorithm, including introducing inertia weights, limiting maximum speed, and other strategies to improve the algorithm's search ability and optimization performance. It also analyzes the convergence and stability of the PSO algorithm. The study in [28] introduces the idea of differential evolution based on PSO algorithm, enabling it to better handle high-dimensional optimization problems. The research in [29] summarizes the application of PSO algorithm in different fields, explores the three-dimensional performance and applicability of the algorithm in solving large-scale complex problems through multiple experimental cases, and proposes corresponding improvement strategies. The study in [30] studied the application of PSO algorithm in the field of data clustering and analyzed their performance and effectiveness in clustering problems. The research in [31] focuses on the application of PSO algorithm in supply chain optimization problems. Introduced the construction of a supply chain optimization model and algorithm design scheme based on particle swarm optimization algorithm, and discussed the advantages of PSO algorithm in supply chain optimization.

Similarly, the Whale Optimization Algorithm (WOA) has also received widespread attention from relevant researchers in [32]. The study in [33] studied the application of improved MVO algorithm in indoor positioning systems, aiming to improve the positioning accuracy of WOA algorithm in visible light systems. Gharehchopogh et al. systematically investigated the latest research progress in WOA. The study introduces the advantages and limitations of the WOA algorithm, and evaluates its application effectiveness in different fields through a series of experiments [34]. The research in [35] proposed an improved WOA based on chaotic mutation and applied it to the optimization process of large-scale complex problems. The performance of the algorithm was demonstrated through various standard test functions and comparative experiments. Based on the review of the above content, we improve the GSO algorithm and compare it with PSO and WOA algorithms.

C. Deep Learning

The study in [36] provides a comprehensive introduction to the development, algorithms, and applications of deep learning. The article discusses the structure and training methods of deep learning models, and proposes some future research directions for deep learning. This study covers the basic principles of deep learning, neural network architecture, parameter optimization methods, and reviews the applications of deep learning in speech recognition, image classification, natural language processing, and other fields. The research in [37] designed a novel deep learning algorithm to improve the accuracy and fairness of deep learning in the decision-making process, thereby optimizing multi-objective optimization problems. The study in [38] focuses on optimizing the dynamic performance of aircraft airfoils and designs a deep learning algorithm for multi-objective optimization, aiming to reduce the gap between the solution results and the Pareto front. The study in [39] designed a recursive neural network to predict the financial risks of enterprises.

III. FINANCIAL RISK MODEL

By summarizing the various indicators related to financial risk prediction in literature [1]-[7]. Based on the Analytic Hierarchy Process, four indicators directly related to financial risk are summarized, namely Funding risk (A1), Investment risk (A2), Operational risk (A3), and Liquidity risk (A4). Furthermore, the four types of risks are divided into 11 indicators that directly constitute the four types of risks, as follows:

- Funding scale (B1)
- Financing time (B2)
- Funding cost (B3)
- Risk of capital investment (B4)
- Profitability (B5)
- Operating capacity (B6)
- Procurement Risk (B7)
- Inventory Shortage Risk (Production Risk) (B8)
- Inventory realization risk (B9)

- Long term fund repayment risk (B10)
- Short term fund repayment risk (B11)

Table I shows the various indicators generated at three levels based on the Analytic Hierarchy Process.

Furthermore, we will use expert back-to-back scoring to determine the importance of each indicator in the C-layer on financial risk impact. In addition, the risk level is divided into six levels, represented by the numbers 1-6, and divide the intervals into [0, 0.2163), [0.2163, 0.3694), [0.3694, 0.4837, 0.6405), [0.6405, 0.8379), [0.8379, 1] representing safety, low risk, low medium risk, medium high risk, and high risk. Based on the collected data on the rationality of fundraising scale, funding availability time, and fund usage time, along with the other 11 indicators listed in Table I, we will Normalize the relevant indicators of 155 companies, The details are shown in Table II.

TABLE I. STRATIFICATION OF FINANCIAL RISK SOURCES BASED ON ANALYTIC HIERARCHY PROCESS

Layer A	Layer B	Layer C
A1-Financing risk	B1-Funding scale	C1-Rationality of fundraising scale
	B2-Financing time	C2-Funding availability time
		C3-Fund usage time
	B3-Funding cost	C4-Comprehensive financing cost
A2-Investment Risk	B4-Risk of capital investment	C5-Capital investment intensity
		C6- Capital loss rate
	B5-Profitability	C7- Product net profit
	B6-Operating capacity	C8- Asset turnover rate
		C9- Product turnover rate
A3-Business risk	B7-Procurement Risk	C10-Supplier stability in the raw material market
	B8-Inventory shortage risk (Production risk)	C11-Insufficient inventory
	B9-Inventory realization risk	C12-Market demand stability
A4-Liquidity risk	B10-Long term fund repayment risk	C13- Asset liability ratio
	B11-Short term fund repayment risk	C14-Cash ratio

TABLE II. NORMALIZATION RESULTS OF EACH INDICATOR

	C1	C2	C3	C4	C5	…	C13	C14
E1	0.8147	0.2784	0.9571	0.7922	0.6787	…	0.2769	0.9502
E2	0.9057	0.5468	0.4853	0.9594	0.7577	…	0.0461	0.0344
E3	0.1269	0.9575	0.8002	0.6557	0.7431	…	0.0971	0.4387
E4	0.7655	0.7093	0.1189	0.7512	0.5472	…	0.1965	0.5852
E5	0.7951	0.7546	0.4983	0.2550	0.1386	…	0.2510	0.5497
…	…	…	…	…	…	…	…	…
E154	0.9171	0.0758	0.5688	0.3112	0.6892	…	0.1066	0.0844
E155	0.2858	0.0539	0.4693	0.5285	0.7481	…	0.9618	0.3997

IV. GLOWWORM SWARM OPTIMIZATION

The GSO algorithm is an algorithm generated by fireflies moving towards a light source. During the optimization process, it randomly generates a group of firefly populations in the search space and assigns an initial brightness value to each firefly individual. Furthermore, each individual firefly updates its position through a movement strategy based on its current position and the brightness information of surrounding fireflies. The goal of moving is to move towards higher brightness in order to find a better solution. Fireflies communicate information between individuals by emitting and receiving light signals. A firefly will emit a light signal, and its brightness value will decrease with increasing distance. Other fireflies determine whether there is a brighter solution around them based on the received light signal and selectively move towards the direction of the light source.

This algorithm optimizes the search process by updating the fluorescence of individual fireflies, calculating their mobility probability, updating their positions, and updating their neighborhood ranges. The specific steps are as follows:

1) Update the fluorescence: Each firefly's luminescence value is equal to the luminescence value from the previous moment plus a certain extraction proportion of the current firefly's fitness value. This is then subtracted by a certain proportion of luminescence value that evaporates over time. The mathematical description is as follows:

$$\beta_x(\delta+1) = (1-\rho)\times\beta_x(\delta) + \chi\times F\left[\beta_x(\delta)\right] \tag{1}$$

where, $\beta_x(\delta+1)$ represents the concentration of fluorescein in individual x of the firefly during $\delta+1$ iterations. ρ is the fluorescence emission coefficient, and χ is the fitness extraction ratio. $F\left[\beta_x(\delta+1)\right]$ is the fitness function value of firefly x during δ iterations.

2) Calculate the mobility probability: During the specific movement of each firefly, it needs to determine its direction based on the luminescence concentration of all neighboring fireflies within its decision radius. $V_{xn}(\delta)$ represents the probability at time δ (iteration) that the firefly moves towards the neighboring firefly. The calculation formula is as follows:

$$V_{xn}(\delta)=\frac{\beta_n(\delta)-\beta_x(\delta)}{\sum\left(\beta_m(\delta)-\beta_x(\delta)\right)} \tag{2}$$

where, $V_{xn}(\delta)$ represents the probability of the x -th firefly moving towards the n -th neighbor firefly individual during the δ -th iteration process.

3) Update the positions: Selecting the maximum movement probability and updating the position: Firefly $D_x(\delta)$ moves a certain distance towards the firefly with the maximum luminescence within its decision radius. The movement formula at time $\delta+1$ is as follows:

$$D_x(\delta+1)=D_x(\delta)+\theta\frac{D_n(\delta)-D_x(\delta)}{\left\|D_n(\delta)-D_x(\delta)\right\|} \tag{3}$$

4) Update the neighborhood ranges: Each firefly adopts an adaptive dynamic decision radius, changing its decision radius based on the density of neighboring fireflies during each iteration. When the neighbor density is low, it increases the decision radius to search for more neighbors. Conversely, when the neighbor density is high, it decreases the decision radius.

V. Problem Solving Approach

Deep neural networks (DNN) are powerful machine learning techniques rooted in the concept of artificial neural networks. These algorithms facilitate the learning and prediction of vast datasets through the combination of multi-layered neurons. Fig. 1. shows the architecture of DNN [40]-[41]. The primary advantage of DNN lies in their adeptness at feature learning, enabling them to automatically extract high-level abstract features from raw data, thereby enhancing the predictive performance of models. While DNN have demonstrated impressive results across various domains, their performance in tasks, such as risk level prediction, continues to be challenged by the optimization of model parameters. To tackle this issue, this study introduces a method based on the GSO algorithm for optimizing parameters within deep learning networks, ultimately enhancing prediction accuracy and robustness.

Within the GSO algorithm, each individual relies on a nearby superior individual to provide guidance during the search process. If there is no such superior individual within the perceptual range, the individual becomes unable to continue the search, rendering the algorithm heavily reliant on these superior individuals. This dependency can potentially slow down convergence speed. Moreover, as an individual approaches the optimal solution, it might oscillate around that solution due to its step size exceeding the remaining distance. This oscillation can also impact the algorithm's performance.

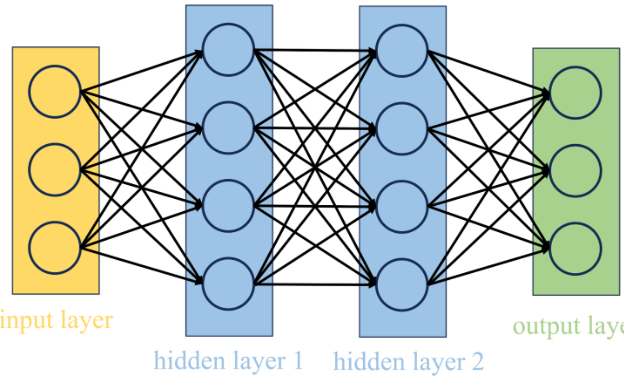

Fig. 1. DNN architecture.

To address these issues, the incorporation of an elite reservation strategy is proposed into the GSO algorithm. This addition aims to enhance the algorithm's convergence speed and accuracy. In the GSO algorithm, the elite strategy involves maintaining the positions of both optimal and suboptimal individuals unchanged while updating the positions of individuals in the population. By combining this enhanced GSO algorithm with deep learning techniques, this study aims to develop an efficient and accurate method for predicting risk levels. Specifically, following these steps:

1) Initialization: Start by randomly generating an initial set of parameters (weights and biases) to form the foundation of the neural network. Simultaneously, configure the parameters of the GSO algorithm, including population size, the number of iterations, step size, and neighborhood threshold.

2) For each generation, perform the following operations:

a) Construct the neural network using the current parameter combination, input the training data, and compute prediction results.

b) Evaluate the fitness of each individual in the population by calculating a fitness function based on the predicted results and the actual risk levels. Each individual corresponds to a neural network, and their fitness is determined by comparing the predicted output of the neural network to the actual values. This comparison can be expressed as either the mean square error (MSE) or root mean square error (RMSE):

$$MSE=\frac{1}{P}\sum_{i=1}^{P}(y_i-y_i)^2 \tag{4}$$

$$RMSE=\sqrt{\frac{1}{P}\sum_{i=1}^{P}(y_i-y_i)^2} \tag{5}$$

Here, P represents the number of training samples, y_i denotes the actual value, and y_i signifies the predicted output value. Our selection for the fitness function is the RMSE.

c) Identify the optimal and suboptimal individual positions based on the fitness function values. Update the location of each individual within the population using a roulette strategy to determine the direction of movement while preserving the positions of the optimal and suboptimal individuals.

3) Repeat step 2 until the termination condition is met (reaching the maximum number of iterations).

4) Create a neural network utilizing the optimal parameter combination, input the test data, and generate predictions.

5) Output the predictions, specifically the risk level, and assess the model.

The algorithm's flowchart is depicted in Fig. 2.

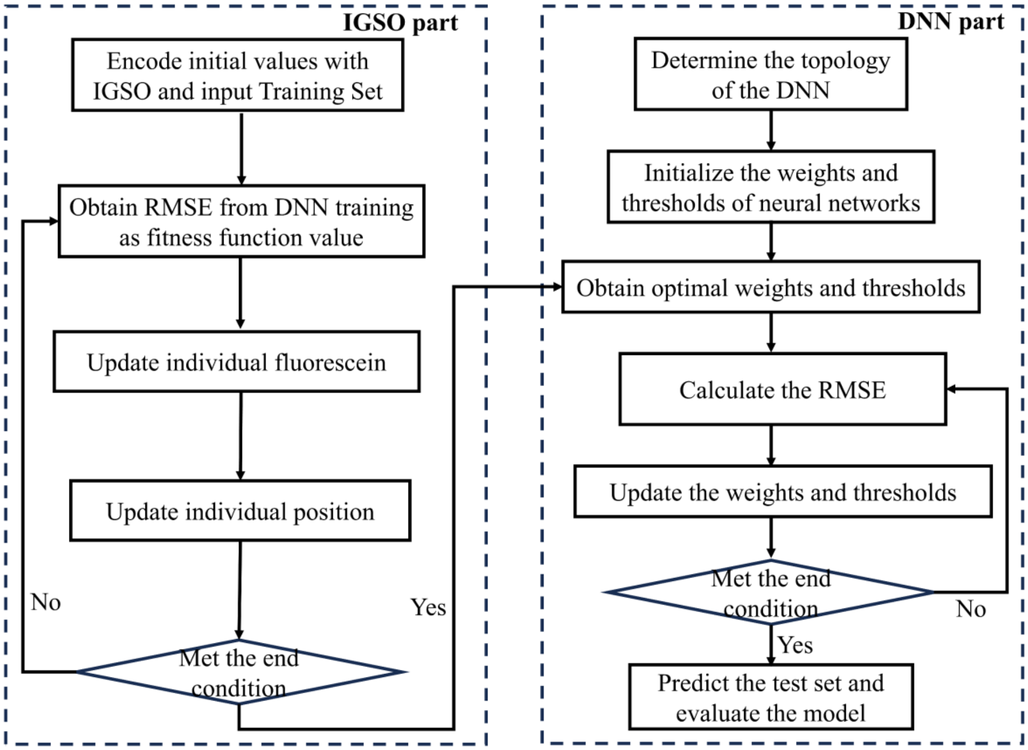

Fig. 2. The flowchart of the algorithm.

VI. Result and Discussion

In this work, data from 155 rural economic development organizations were selected for the study. Out of these, 110 sets of data were allocated for the training set, while the remaining 45 were used for the test set. For the IGSO algorithm, the number of iterations to 50 and the population size to 35 are set. We train the model using a training set and assess its performance using RMSE. After obtaining a well-trained model, we can input risk-related data from other companies to evaluate the level of risk for the company. Our objective is to have the model predict the company's risk level as accurately as possible, so we aim to obtain a model with a smaller RMSE through training. Our simulation experiments rely on MATLAB 2022b, and we have a high-performance computer system with the following key specifications: CPU is i9-13900KS; GPU is NVIDIA GeForce RTX 4090.

Initially, a combination of DNN and the IGSO algorithm is employed to train the training set. To provide a comparative analysis with the enhanced IGSO algorithm, we also utilized the Whale Optimization Algorithm (WOA) and Particle Swarm Optimization Algorithm (PSO) for optimizing the DNN. Fig. 3. illustrates the iteration curves of these three optimization algorithms after a single run.

From the Fig. 3, it is evident that the objective function values obtained after iterations using IGSO are superior to those of WOA and PSO, converging to values of 0.01, 0.33, and 0.18, respectively. In terms of convergence speed, IGSO reaches convergence around the 10th generation, which is notably faster than WOA and PSO. This suggests that models optimized through IGSO can provide more accurate predictions for the input training set, and the training speed of the model will also be improved.

To assess the algorithm's stability, a total of 30 runs are conducted and compared the iteration curves of the optimal, worst, and average values for each generation, as depicted in Fig. 4 to Fig. 6. Upon comparing these figures, it becomes evident that IGSO outperforms WOA and PSO in terms of both convergence accuracy and speed. This observation underscores the robust stability of the IGSO algorithm. Across the 30 repeated runs, the average objective function value after convergence was at 0.05, surpassing the respective values of 0.40 for WOA and 0.28 for PSO. This observation underscores the robust stability of the IGSO algorithm.

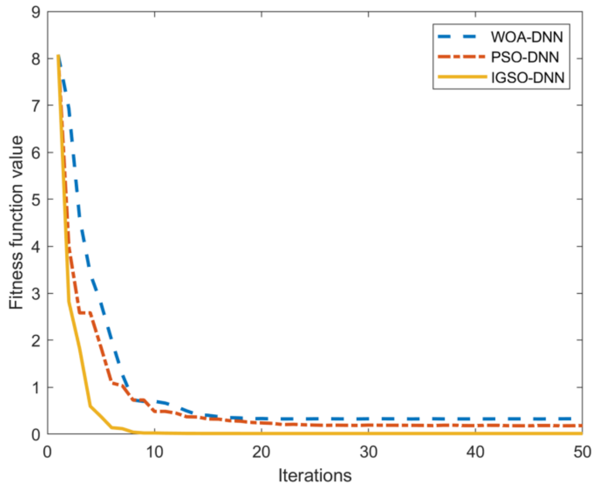

Fig. 3. Plot of iteration curves for one run.

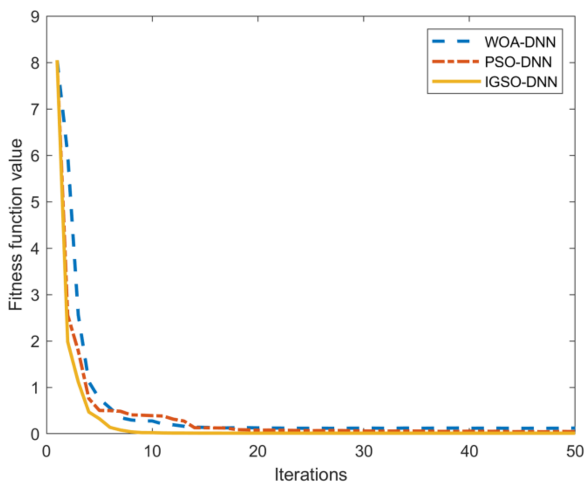

Fig. 4. Iterative curve of optimal values per generation in 30 runs.

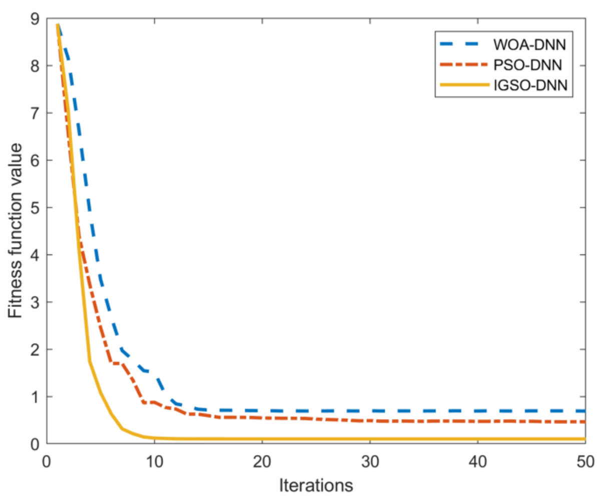

Fig. 5. Iterative curve of worst values per generation in 30 runs.

To evaluate the predictive performance following the successful optimization of DNN parameters using the IGSO optimization algorithm, predictions on a set of 45 test cases are conducted, with the results presented in Fig. 7. Furthermore, these results with predictions made using DNN optimized are compared through PSO and WOA, as shown in Fig. 8 and Fig. 9. The red line indicates that the true value deviates from the predictive value. Risk level is between 2 and 5.

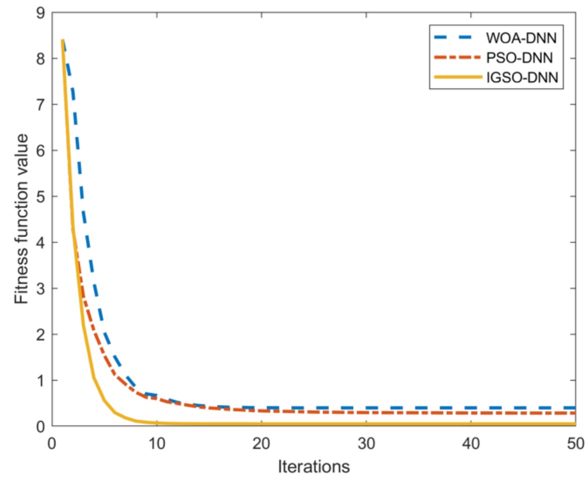

Fig. 6. Iterative curve of mean values per generation in 30 runs.

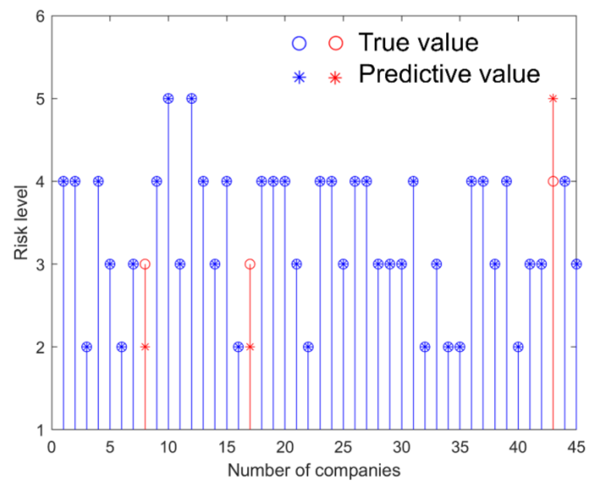

Fig. 7. Plot of true vs. predicted values for test set based on IGSO-DNN.

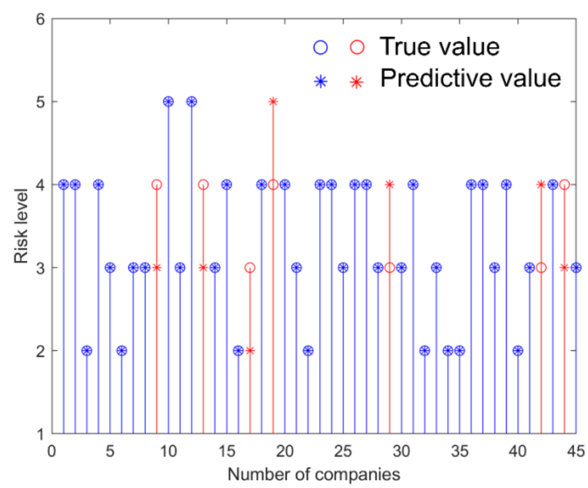

Fig. 8. Plot of true vs. predicted values for test set based on PSO-DNN

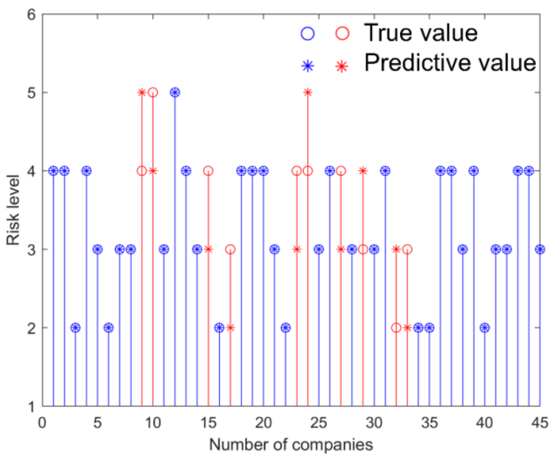

Fig. 9. Plot of true vs. predicted values for test set based on WOA-DNN.

From the results, it is evident that the DNN optimized through IGSO also yields more accurate predictions for the test set. To enhance its demonstrative precision, we further calculated the error count and error rate for risk level predictions using IGSO-DNN, PSO-DNN and WOA-DNN, as summarized in Table III, Table IV, and Table V.

Notably, the IGSO-optimized DNN exhibits superior predictive capabilities, low-medium risk error rate is 12.5% and medium risk error rate is 5.26%, and the remaining risk levels can be accurately predicted. While for PSO-DNN, low-medium risk error rate and medium risk error rate is 18.75% and 21.05%, respectively. For WOA-DNN, its low-risk error rate is 12.5%, low-medium risk error rate is 18.75%, medium risk error rate is 26.32% and medium-high risk error rate is 50%. Compared to WOA-DNN and PSO-DNN, IGSO-DNN exhibits excellent predictive capabilities across various risk ranges.

TABLE III. RISK PREDICTION RESULTS FOR IGSO-DNN

	Safe	Low risk	Low-medium risk	Medium risk	Medium-high risk	High risk
Test sample (True value)	0	8	16	19	2	0
Number of errors (Predictive value)	0	0	2	1	0	0
Error rate (Predictive value)	0	0	12.5%	5.26%	0	0

TABLE IV. RISK PREDICTION RESULTS FOR PSO-DNN

	Safe	Low risk	Low-medium risk	Medium risk	Medium-high risk	High risk
Test sample (True value)	0	8	16	19	2	0
Number of errors (Predictive value)	0	0	3	4	0	0
Error rate (Predictive value)	0	0	18.75%	21.05%	0	0

TABLE V. RISK PREDICTION RESULTS FOR WOA-DNN

	Safe	Low risk	Low-medium risk	Medium risk	Medium-high risk	High risk
Test sample (True value)	0	8	16	19	2	0
Number of errors (Predictive value)	0	1	3	5	1	0
Error rate (Predictive value)	0	12.50%	18.75%	26.32%	50%	0

VII. CONCLUSION

This study focuses on the financial risk management issues of rural economic development organizations, focusing on the financial risk management system used for rural economic development organizations, aiming to help rural economic development organizations avoid financial risks. At the same time, an IGSO algorithm was designed to optimize CNN, aiming to improve the accuracy of deep learning algorithms in predicting financial risks. Finally, data from 110 rural economic development organizations were used as a training set, while data from 45 rural economic development organizations were used as a testing set. The simulation results showed that the DNN optimized by IGSO showed excellent predictive ability, with a medium to low-risk error rate of 12.5% and an average accuracy improvement of 3.73% compared to PSO-DNN and WOA-DNN; The medium risk error rate is 5.26%, with an average accuracy improvement of 19.44% compared to PSO-DNN and WOA-DNN; In addition, IGSO DNN can accurately predict other risk levels. In future research, new algorithms will be further developed to improve the accuracy of predictions. In addition, the applicability of risk prediction models is also a potential research direction.

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