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FINANCIAL RISK PREDICTION MODELS FOR LISTED COMPANIES BASED ON IWOA-LSTM

SHA LI, XUAN CHEN*, AND TAIXIN WANG

Abstract. Managing corporate financial risk has always been the focus of research in the financial industry. Long short-term memory (LSTM) has been slowly and gradually applied to financial data analysis owing to its advantages in time-series data processing, but its performance has been affected by its parameters. Therefore, This study aimed to propose an IWOA-LSTM model for predicting financial risk using an improved whale optimization algorithm–optimized LSTM. First, we selected the indicators reflecting the financial characteristics of manufacturing companies using factor analysis; second, we improved WOA from two aspects: population initialization and convergence factor. We used two parameters, the number of neurons in the hidden layer and the time step, of the LSTM model to find the optimal value using WOA. Finally, we singled out the public financial data of listed manufacturing companies in China as the research object., and the results show that the predicted value of the model is in the range of 1% from the true value, which indicates that the model has certain advantages in the prediction of corporate financial risk.

1. Introduction

At present, the international financial environment is in an unstable state because of regional wars, so managing the financial risk of listed enterprises efficiently is now a vital research direction in the financial industry [22]. In recent years, various information technologies have been widely used in financial data statistics, analysis, and risk prediction. Especially in risk prediction, backpropagation (BP), support vector machine (SVM), and logistic techniques have produced improved results. However, these techniques may result in low precision and weak prediction effects due to the strong temporality of financial data. Many scholars have tried to optimize the structure of these techniques, but have still not obtained satisfactory results. Therefore, artificial intelligence techniques should be used in early warning methods assessing financial risks. The long short-term memory (LSTM) model [6] is a variant of recurrent neural network (RNN) commonly used to deal with sequence data. It has the advantages of long time dependence, anti-gradient vanishing, and effective long sequence training, consistent with the financial time-series data. However, the parameters of the model are critical to the prediction performance. For these reasons, we proposed a financial risk prediction model based on the whale optimization algorithm–LSTM (WOA-LSTM). This model involved the following steps:

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*Corresponding author.

(1) Factor analysis was used to obtain indicators truly reflecting the financial characteristics of the company.
(2) The WOA was optimized for initialization and convergence factors.
(3) Given that the accuracy of current LSTM model parameters is often affected by artificial factors, we proposed using an enhanced WOA to optimize these parameters.
(4) In the simulation experiment, the effectiveness of the proposed algorithm was validated for several relatively new financial forecasting algorithms.

The article is organized as follows: Section 2 reviews the current research related to financial risk; Section 3 presents the IWOA-LSTM model; Section 4 outlines the corporate financial early warning risk model; Section 5 discusses the simulation experiments conducted; and Section 6 presents the conclusions.

2. Related work

The techniques used in the early warning model on corporate financial risk are mainly related to three areas: multivariate logistic regression, neural network application, and artificial intelligence techniques. The progress in each of these three areas is discussed as follows:

(1) Multivariate logistic review methods. These methods mainly use techniques such as SVM, least squares support vector machine (LSSVM), logistic, and regression techniques to perform studies on financial risk prediction. For example, Hua et al. [8] designed a hybrid financial risk prediction model of logistic and SVM, and the findings exhibited certain enhancements in the prediction. Jabeur [9] proposed the use of LSSVM for corporate financial risk prediction. Some previous studies [4, 25] proposed financial risk prediction using logistic regression and multivariate discriminant methods, and the results demonstrated a certain degree of feasibility. Lizares [14] adopted the SVM method to analyze publicly traded companies. The aforementioned methods can be applied to early financial risk prediction, but they have many deficiencies in data pre-processing, model parameter selection, and so forth, and hence cannot adapt to the current development in financial crisis prediction technology.
(2) Neural network methods. These methods use the BP neural network for financial risk prediction. Ohlson [19] first applied BP neural networks in the financial risk early warning and achieved good results. A few previous studies [10,12,21] used the BP neural networks from different aspects for predicting financial risk. Some other studies [7, 11, 24] proposed meta-heuristic algorithms such as self-organizing maps, genetic algorithms, and particle swarm optimization combined with BP neural networks for predicting the early warning type of financial risk. The simulation results illustrated an obvious improvement effect of these methods compared with the BP neural network alone. However, the technology was prone to overfitting phenomenon, whereas the effect of initial weights, learning rate, and other parameters on prediction was not good.

(3) Artificial intelligence technology methods. As artificial intelligence technology is widely used in various industries, scholars are now using these technologies in the field of financial forecasting. Yan et al. [23] adopted the LSTM neural network to analyze the capital of listed enterprises, and the findings revealed a better prediction effect compared with the BP neural network. Liu et al. [18] proposed a deep learning and BP neural network–based method and predicted the financial risk of listed enterprises in Shanghai, China, in 2021 through this model. Rostamian et al. [20] proposed a convolutional neural network–LSTM (CNN-LSTM)-based model for predicting the financial crisis of listed companies, and the core idea was to combine the powers of CNN as well as LSTM models. Baek [1] used the optimized parameters of the CNN-LSTM model based on genetic algorithms for predicting financial crises. Yan et al. [23] adopted a model based on the LSTM neural network for predicting financial assets. Hansun et al. [3] proposed a prediction model based on RNN–LSTM for the financial industry -. Further, previous studies [13, 15] provided some new ideas. The results showed that the use of LSTM models for predicting financial data in terms of time series does have a certain effect, enriching the current financial risk of listed companies as a means of early warning; however, optimizing the model structure and improving the model prediction performance are some current research directions that need to be explored.

3. IWOA-LSTM model

As current financial data are usually characterized by time series, such as changes in corporate revenue, profit, and other indicators at different points in time, the use of the LSTM model can effectively and efficiently capture the long-term dependencies and patterns in the time series, thus providing a powerful and effective tool for financial risk prediction.

3.1. **Whale optimization algorithm.**

WOA [16] is a nature-inspired algorithm widely used in various fields in recent years. This algorithm has good performance characteristics, and many scholars use it to optimize a variety of scenario problems. The central idea of this algorithm is to simulate the life habit–inspired acquisition of whales, a large group of predators in the ocean. Whales mainly collaborate to complete their life in the deep sea, which is roughly divided into three primary areas: surrounding the prey, bubble attacking the prey, and searching for prey.

(1) Surrounding the prey
The whale population uses encircling strategies when acquiring the prey to obtain food in the ocean. In WOA, the current position of the whole population is usually set to be the area of food aggregation so that other whales can approach the aggregation position, and the process of encirclement of the prey can be completed. Each individual whale position is updated according to Eq. 3.1.

$$X(t+1) = X_p(t) - A \cdot \left| C \cdot X_p(t) - X(t) \right|, \tag{3.1}$$

where t is the position of the pth whale in the tth iteration, and $X_p(t)$ and $X(t+1)$ are the positions of the tth and $t+1$th whales, respectively. Again, t is the number of iterations, $X_p = \left(X_p^1, X_p^2, \cdots X_p^D\right)$ is the location of the food source in the ocean, and $X(t)$ signifies the position of the individual whale at the tth iteration. $A \cdot |C \cdot X_p(t) - X(t)|$ is the encircling step. The parameters A and C are defined as follows:

$$A = 2a \cdot rand_1 - a, \tag{3.2}$$

$$C = 2 \cdot rand_2, \tag{3.3}$$

where $rand_1$ and $rand_2$ represent random values with the range (0,1), and a represents the convergence parameter varying between (2,0), expressed as follows:

$$a = 2 - 2t/t_{\max}, \tag{3.4}$$

where t represents the current iteration number and t_{max} is the upper limit of iterations.

(2) SBubble attacking the paey
In mathematical description, the behavior of whales performing predation is mainly divided into contraction encirclement and spiral bubble attacking. The former has been implemented using Eqs. 3.2 and 3.4, and the latter is expressed as follows:

$$X(t+1) = D' \cdot e^{lb} \cdot \cos(2\pi l) + X_p(t), \tag{3.5}$$

where $D' = |X_p(t) - X(t)|$ represents the gap between the ith whale and its prey, b is used as a constant to define the spiral shape, and l represents a random value between [-1,1]. It should be ensured that the probability of both shrink-wrapped and bubble-attack behaviors is set to 0.5 as the whales move around the prey in a spiral pattern within a shrink-wrapped circle.

(3) Searching for prey
In the sea, whales search for food in a randomized way. Essentially, an individual whale searches for food in a random manner based on the location of other individuals in the group, as expressed in Eq. 3.6

$$X(t+1) = X_{rand}(t) - A\left|C \cdot X_{rand}(t) - X(t)\right|, \tag{3.6}$$

where $X_{rand}(t)$ is the location of a randomly chosen whale from the existing population.

3.2. **LSTM Model.** LSTM is a special type of RNN model that solves the problems of gradient vanishing and gradient explosion in traditional RNNs when handling long sequence data. It better addresses long-term dependencies by introducing a gating mechanism, enabling more effective processing of time-series data.The model's equations are as follows:

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), \tag{3.7}$$

$$i_t = \sigma(W_i x_t + U_f h_{t-1} + b_i), \tag{3.8}$$

$$c_t' = Tanh(W_c x_t + U_c h_{t-1}), \tag{3.9}$$

$$c_t = f_t c_{t-1} + i_t c_t', \tag{3.10}$$

$$h_t = o_t Tanh(c_t), \tag{3.11}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o), \tag{3.12}$$

where x_t represents the t-time data input to the layer, h_t is the hidden state input at time t, represents the forget gate, i_t is the input gate, o_t is the output gate, c_t denotes the memory cell, W and U represent weights, b is the offset, and σ and $Tanh$ denote the Sigmoid and Tanh activation functions, respectively.

3.3. **Improved WOA.** We further improved the performance of the whale algorithm in terms of population initialization and adaptive convergence factor. Optimizing the population size primarily aimes to enhance the algorithm's exploration ability and boost population diversity. At the same time, optimizing the convergence factor focuses on balancing global search and local exploitation capability to accelerate the algorithm's convergence speed.

(1) Population initialization
The diversity of initial population significantly improves the convergence rate and the precision of the population-based intelligence algorithms. However, usually, the whale optimization algorithm initializes the population randomly, which may not ensure sufficient diversity. To address this issue, the concept of chaotic optimization is introduced, expressed as follows:

$$x_{j+1}^i = \mu x_j^i \left(1 - x_j^i\right), \tag{3.13}$$

where μ is a chaos parameter with a value range of (0,4). In this study, we compared the adaptation value of each individual whale after chaotic operation with the original individual adaptation and kept the individual with a large adaptation value.

(2) Adaptive convergence factor
In the WOA algorithm, A is an important parameter related to the possibility of the algorithm finding the optimal solution. This parameter mainly adjusts the local and global search methods capabilities of the WOA algorithm. In Eq. 3.2, the parameter A is mainly affected by the factor a. When a gradually decreases from 2, the algorithm exhibits global search ability and obtains the current optimal solution. When the range of a gradually decreases and approaches 0, the algorithm's local search ability gradually increases. Therefore, a is dynamically adjusted to find an optimal balance of both global and local solutions. Also, F is dynamically adjusted to achieve an ideal balance between global and local solutions, maximizing the capability of the algorithm to find the best solution. Therefore, factor a is expressed as follows:

$$a = a_0 + \frac{t}{t_{\max}} \times \frac{1}{f(x_i^t) + \zeta}, \tag{3.14}$$

where t_{max} represents the upper limit of iterations, t denotes the current iteration number, $f(x_i^t)$ represents the fitness value of the current individual

i, ζ is a random number between [1,2], and a_0 is the initial value of a, which is set as 1.

3.4. **Optimizing LSTM parameters using IWOA.** The performance of the LSTM network is influenced by the count of hidden neurons m and the time step c [5]. We used the WOA algorithm to optimize these two parameters to obtain optimal values and enhance the model's performance and generalizability. The value of the time step is usually set empirically [2]. Further, m is expressed as follows:

$$m = \sqrt{\alpha + \beta} + q, \tag{3.15}$$

where α represents the number of nodes in the output layer and β in the input layer, and q is a constant between [0,10]. Therefore, we used m and c as a set of individual whales to identify the optimal parameters using the WOA algorithm.

4. Enterprise financial early warning risk model

We selected a preliminary set of indicators reflecting the financial risk of manufacturing industry, performed factor analysis to identify key indicators and data normalization using normalization methods, and finally conducted risk prediction using the IWOA-LSTM model.

4.1. **Financial indicator methodology.** We performed factor analysis for indicator selection and compared the result with that of principal component analysis. The following considerations were made for the factor analysis: first, it can identify the common hidden factors in linking multiple variables, which is more relevant to financial indicators; second, it selects common factors with full consideration of the correlation structure between variables; and finally, it has a higher degree of different sample or time-series stability and can capture the key information in financial data.

4.2. **Screening of financial risk indicators.** To accurately obtain the financial risk indicators of publicly traded manufacturing firms, we first selected the initial set of indicators reflecting the financial characteristics; second, we used the factor analysis method to eliminate the existence of internal correlation indicators to avoid the complexity of the model analysis; and finally, we obtained the key indicator set.

Table 1 shows the 17 core indicators reflecting the financial characteristics. These indicators were found to have a relatively strong correlation with each other. Therefore, the decoupling and weak correlation strategy was adopted. On the one hand, this strategy can reduce the analytical efficiency due to the repetitive calculations brought about by the strong correlation indicators. On the other hand, high-dimensional feature training analysis can enhance the complexity of the results of the early warning of financial risk. After using factor analysis on Table 1 to obtain Table 2, the factor commonality value of X5 and X7 was less than 0.4, indicating that the factors were weakly associated with the research project. Moreover, it was almost impossible to extract the information from the research project and the validity of the results was not good. Therefore, these two variables were excluded. The screened financial indicators are shown in Table 3.

Table 1. Unscreened set of financial indicators

Code	Financial indicators	Indicator definition
X1	Debt-to-asset ratio	Total debt to total assets
X2	Debt-to-equity ratio	Total debt to total shareholder's equity
X3	Fixed asset performance ratio	Sales revenue to average net fixed assets
X4	Total asset performance ratio	Net sales revenue to average total assets
X5	Inventory performance ratio	Cost of goods sold to average inventory
X6	Operating income growth rate	Growth in operating income compared to the first half of the year
X7	Capital accumulation rate	Equity growth to equity at the start of the year
X8	Total profit growth rate	Change in total profit to last year's total profit
X9	Operating profit margin	Operating profit to operating income
X10	Gross profit margin	Gross profit to sales revenue
X11	Return on net assets	Net profit to net assets
X12	Asset preservation rate	Change in equity after adjusting for external factors
X13	Cash flow ratio	Cash flow from operations to total assets
X14	Debt-to-tangible asset ratio	Total debt to tangible assets
X15	Total asset growth ratio	Increase in total assets to beginning total assets
X16	Fixed asset formation rate	Investment in fixed assets to total investment
X17	Return on assets ratio	Net profit to average total assets

4.3. **Data normalization for financial risk indicators.** Financial indicators differ significantly depending on the unit of measurement. This study adopted the "minimum–maximum normalization" method to normalize the financial data, transforming the data values into the [0,1] interval to reduce the impact of significant variations in financial risk indicators on model prediction outcomes. It used SPSS software to normalize the initial financial data, and the processing formula used was as follows:

$$x^* = \frac{x - \min}{\max - \min}, \tag{4.1}$$

where x and x^* are the initial sample data and normalized data, respectively, and *max* and *min* are, respectively, the highest and the lowest values in the initial data. Table 4 presents the financial crisis forecasting process.

TABLE 2. Factor commonality corresponding to each variable after rotation

Factor	Commonality
Asset liability ratio	0.795
Equity ratio	0.692
Fixed assets performance ratio	0.954
Total assets performance ratio	0.673
Inventory performance ratio	0.128
Operating income growth ratio	0.429
Capital accumulation ratio	0.319
Total profit growth ratio	0.972
Business profit margin ratio	0.693
Gross profit margin on sales	0.703
Return on net assets	0.932
Rate of preservation and appreciation of assets ratio	0.916
Cash flow ratio	0.983
Ratio of debt to tangible assets ratio	0.974
Total assets growth ratio	0.894
Formation rate of fixed assets ratio	0.983
Return on assets ratio	0.962

TABLE 3. Set of financial indicators

Code	Financial indicators
X1	Asset liability ratio
X2	Equity ratio
X3	Fixed assets performance ratio
X4	Total assets performance ratio
X5	Operating income growth ratio
X6	Total profit growth ratio
X7	Business profit margin ratio
X8	Gross profit margin on sales
X9	Return on net assets
X10	Rate of preservation and appreciation of assets ratio
X11	Cash flow ratio
X12	Ratio of debt to tangible assets ratio
X13	Total assets growth ratio
X14	Formation rate of fixed assets ratio
X15	Return on assets ratio

5. SIMULATION EXPERIMENT

5.1. **Experimental environment and evaluation indicators.** We built a deep learning framework based on TensorFlow to better examine the effect of the financial risk early warning model proposed in this study. The hardware platform was configured as follows: the central processing unit was Core I7, the memory was 32GDDR4, the capacity of the hard disk was 2T, the system was Win10, and the simulation environment adopted the Spyder compilation tool and Python programing. The main parameters of the LSTM model are shown in Table 5.

In this study, publicly traded manufacturing companies were chosen as the research focus (part of the data is shown in Fig. 1. A total of 90 selected companies

TABLE 4. Financial crisis forecasting steps

Step 1:	Initialization. Specify the maximum iteration count, determine the risk of financial levels. Correspond each set of m and c parameters in the LSTM model to an individual whale.

Step 2:	Define the fitness function.
	Function FitnessFunction (m, c):
	    Create the LSTM model
	        Train the model
	        Predict and calculate the mean square error
	Return the mean square error

Step 3:	Data preparation. Collect the public data of the enterprise from year $T-5$ to year $T-2$, and select the financial risk indicators according to the factor analysis method.
Step 4:	Data set division. Split the data proportionally into training and test sets.

Step 5:	Whale algorithm optimization.
	WhaleOptimizationAlgorithm (FitnessFunction):
	  Initialize whale individuals according to chaotic thinking
	  Set the optimal fitness function value to infinity
	  Set the optimal position to be empty
	  For each iteration from 1 to maximum iteration count:
	    evaluate the fitness value of each whale
	    Identify the current best individual
	    If the current best is better than the historical optimal:
	      Update the historical optimal
	    Update the whale position (global and local search)
	    If the iteration count is reached, proceed to Step 6.
	      Else: return to Step 5.

Step 6:	Obtain the optimal parameters.
Step 7:	Train and validate the LSTM model. Utilize the optimal set of parameters to build the LSTM model and train it using the training dataset.
Step 8:	Evaluate and output the results. Predict and calculate the accuracy rate on the test set. If the accuracy rate $\geq$ the set threshold: Output the financial risk prediction results for listed companies. Else: Prompt that the requirement is not met and retrain.

TABLE 5. Initial parameters

Parameter name	Assigned value	Parameter name	Assigned value
LSTM layers	2	Hidden units	32
Loss function	Mean squared error	Learning rate	0.001
Optimization algorithm	Adam	Number of epoch	500

from the Chinese manufacturing sector were chosen as research sample from the WIND database from 2017 to 2020. Of these, 30 samples incurred operating losses for two consecutive years (labeled special treatmen-ST) and 60 samples were in normal condition (labeled non-ST). The training and test samples were allocated in a ratio of 2:1. That is, the training sample comprised 20 ST enterprises and 40 non-ST enterprises, and the test sample comprised 10 ST enterprises and 20 non-ST enterprises.

We chose mean square error (MSE) and mean absolute error (MAE) metrics as the evaluation metrics of the algorithm to further validate the performance of the model in this study. The results are shown in Table 6.

year	证券代	行业代	Size	Lev	ROA	ROE	ATO	Cashflo	REC	INV	FIXED	Growth
2000	000002	K70	22.45	0.472516	0.061516	0.121745	0.747989	0.015305	0.091829	0.622391	0.060169	0.317068
2021	000002	K70	28.29301	0.797398	0.019995	0.102528	0.237825	0.002122	0.002447	0.554831	0.006613	0.080375
2021	000004	I65	20.82814	0.146164	-0.38037	-0.42292	0.216103	0.002793	0.333705	0.018553	0.002203	0.02999
2000	000005	S90	21.42669	0.58385	-0.00458	-0.01098	0.071791	0.010049	0.424982	0.086891	0.18121	0.076525
2000	000006	K70	22.05505	0.666313	0.038701	0.111577	0.534123	0.012019	0.263447	0.418928	0.072248	-0.03026
2021	000006	K70	23.88456	0.65322	0.028358	0.06909	0.158243	-0.16417	0.000801	0.682908	0.0018	0.052419
2000	000007	K70	20.67396	0.855058	-0.17587	-0.78584	0.051356	-0.02291	0.174141	0.129517	0.216035	-0.66646
2000	000008	I64	19.48824	0.572953	0.067682	0.160131	0.389843	0.031406	0.340661	0.025351	0.209181	0.122499
2021	000008	C37	23.23931	0.568954	-0.10939	-0.22971	0.175724	0.037059	0.225272	0.090185	0.033334	0.155036
2000	000009	S90	22.26319	0.700563	0.011094	0.038771	0.133404	0.030268	0.116419	0.557997	0.081911	-0.25747
2021	000009	S90	24.33616	0.577624	0.051041	0.121721	0.509313	-0.00753	0.090821	0.273535	0.132939	0.656944
2021	000010	E48	22.2466	0.812883	0.009656	0.046871	0.432245	-0.01205	0.591895	0.038226	0.004014	0.247323
2021	000011	K70	23.40305	0.689266	0.073668	0.237424	0.335356	-0.12435	0.018621	0.625702	0.007418	0.094434
2000	000012	C30	21.76172	0.330891	0.060289	0.092906	0.39239	0.114446	0.071385	0.16258	0.607012	0.14195
2021	000012	C30	23.71596	0.404872	0.082557	0.138887	0.720688	0.195698	0.036637	0.054857	0.429628	0.277173
2021	000014	K70	21.65498	0.608645	0.019704	0.050313	0.258111	-0.02855	0.000249	0.710799	0.009706	0.851127
2000	000016	C39	23.03213	0.615045	0.025126	0.065847	0.908889	-0.00055	0.103619	0.490868	0.121297	-0.11004
2021	000016	C39	24.409	0.744174	0.017976	0.077116	1.094286	0.020283	0.085211	0.102034	0.100573	-0.02473
2021	000017	C37	18.39396	0.753473	-0.01734	-0.06605	1.747659	0.160984	0.481188	0.084719	0.035323	0.402088
2000	000019	C15	19.87021	0.320259	0.023894	0.037153	0.158032	0.062382	0.063047	0.032702	0.160117	0.069245
2021	000019	F51	22.76053	0.387596	0.058256	0.091931	1.353837	0.057421	0.036905	0.451211	0.277436	-0.14683
2000	000020	C39	19.96177	0.358989	0.006117	0.009657	0.251657	0.009679	0.142308	0.159358	0.50852	-0.20625
2021	000020	C39	20.30765	0.479568	0.011186	0.021191	1.189102	-0.01867	0.194982	0.137265	0.28471	0.106787
2000	000021	C39	22.07778	0.398947	0.03918	0.066371	1.004017	-0.11343	0.318934	0.079282	0.24929	0.187295
2021	000021	C39	24.02091	0.575808	0.034265	0.085616	0.677365	0.032075	0.102484	0.131077	0.15746	0.101623
2000	000023	E47	20.53519	0.649752	0.024726	0.068166	0.328002	0.02952	0.233004	0.19607	0.158435	-0.14725
2021	000023	C30	21.4956	0.741732	-0.01165	-0.04491	0.658763	0.065586	0.355848	0.059564	0.065187	-0.17009
2021	000025	F51	21.34365	0.216415	0.074019	0.092935	0.285038	0.068084	0.00973	0.013677	0.058849	0.198155
2000	000026	C35	20.47734	0.230114	0.018798	0.025282	0.315512	-0.00497	0.153171	0.257139	0.07228	-0.09575
2021	000026	F52	22.13683	0.266957	0.095423	0.133441	1.290084	0.133132	0.094606	0.498749	0.085023	0.235727
2000	000027	D44	22.74406	0.42321	0.096943	0.173224	0.365817	0.164377	0.100952	0.018667	0.534099	0.457315

FIGURE 1. Data for selected listed manufacturing companies

$$MSE = \frac{1}{n} \sum_{k=1}^{n} (y_k - y_k^*)^2 , \tag{5.1}$$

$$MAE = \frac{\sum_{k=1}^{n} |y_k - y_k^*|}{n}, \tag{5.2}$$

where n is the total number of predicted samples, y_k is the actual value of the kth sample, and y_k^* is the corresponding predicted value.

We have chosen several different newer meta-heuristic algorithms gray wolf optimization (GWO), chicken swarm optimization (CSO), and wolf pack algorithm

(WPA) which are often used currently to compare with the algorithms in this paper.These four algorithms are optimized to optimize the number of hidden neurons and time step parameter of the LSTM model respectively.The results obtained are shown in Table 6. From the results in the table, it can be found that the MSE value of IWOA-LSTM is lower than the other three algorithms, while the MAE value is higher than CSO-LSTM and GWO-LSTM but the difference is not much, in the number of hidden neurons, this paper's algorithm is only excess of WPA-LSTM algorithm's 10, but it is much lower than the CSO-LSTM and GWO-LSTM. in the time step number, both this paper's algorithm and WPA-LSTM have the smallest number. From the result comparison results, IWOA-LSTM algorithm has better performance.

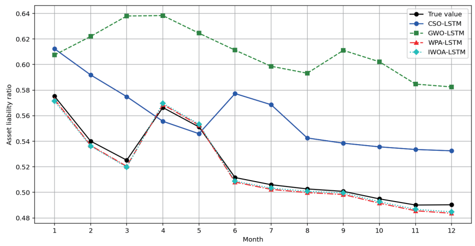
Table 6. Performance of different algorithms for optimizing LSTM models

Algorithm	MSE	MAE	Hidden Units	Time steps
CSO-LSTM	0.05311	0.24819	93	7
GWO-LSTM	0.05408	0.24319	80	10
WPA-LSTM	0.05744	0.79950	56	5
IWOA-LSTM	0.46250	0.25230	66	5

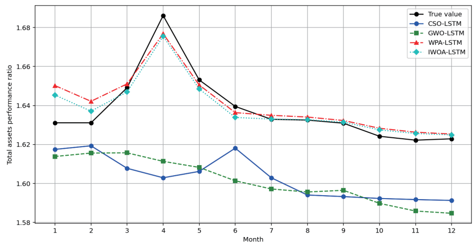
5.2. **Analysis of financial risk prediction performance.** Financial risk early warning is based on historical data for financial prediction. The financial operation of the enterprise is determined using the prediction results of important financial indicators to provide early warning. This paper selects four indicator data from one enterprise, namely the Asset Liability Ratio, Total Assets Turnover Ratio, Cash Flow Ratio, and Operating Income Growth Ratio, and validates the prediction results through four different models. Using monthly financial data from 2020 to 2023, the paper predicts the results for each month of 2024 and compares them with the actual values. From the overall results shown in the figures, the IWOA-LSTM model demonstrates better predictive performance across the four indicators. In Fig. 2a, both IWOA-LSTM and WPA-LSTM show minimal deviations from the actual values each month, significantly outperforming CSO-LSTM and GWO-LSTM. In Fig. 2b, both IWOA-LSTM and WPA-LSTM exhibit some discrepancies from the actual values, with IWOA-LSTM occasionally having lower accuracy than WPA-LSTM in certain months. In Fig. 2c, both IWOA-LSTM and WPA-LSTM again show minimal deviations from the actual values each month. In Fig. 2d, both IWOA-LSTM and WPA-LSTM display some deviations from the actual values, particularly after May, where there is a noticeable bias. Overall, the IWOA-LSTM model achieves a prediction accuracy of around 1%, demonstrating good performance.

6. Conclusions

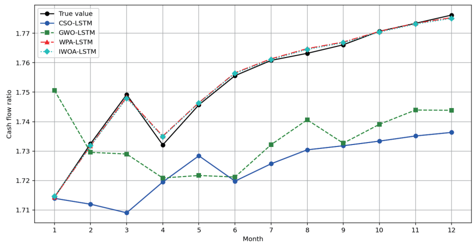
In this study, we explored how to accurately predict the financial crisis as the starting point. Taking the listed textile enterprises as the research object, we proposed a financial risk prediction model based on the IWOA-LSTM model and



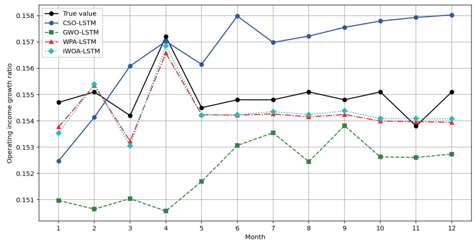
(A) Forecasted results of the asset liability ratio



(B) Forecasted results of the total assets performance ratio



(C) Forecasted results of cash flow ratio



(D) Forecasted results of operating income growth ratio

FIGURE 2. Predicted results for the four indicators

achieved improved results. However, the prediction results of the model may be affected by factors such as macroeconomic environment, market passivity, industry competition, and others. Our future studies will focus on sensitivity analysis and the practical aspects of the neural network model proposed in previous studies [14, 16, 17].

REFERENCES

[1] H. Baek, *A CNN-LSTM stock prediction model based on genetic algorithm optimization*, AsiaPacific Financial Markets **31** (2024), 205–220.

[2] D. Chicco, M. J. Warrens and G. Jurman, *The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation*, Peerj Computer Science **7** (2021): e623.

[3] S. Hansun and J. C. Young, *Predicting LQ45 financial sector indices using RNN-LSTM*, Journal of Big Data **8** (2021) 104–116.

[4] E. Ul Hassan, Z. Zainuddin and S. Nordin, *A review of financial distress prediction models: logistic regression and multivariate discriminant analysis*, Indian-Pacific Journal of Accounting and Finance **1** (2017), 13–23.

[5] Y. He, X. Xu, Y. Cai and M. Cheng, *An evaluation of the effectiveness of three early-warning models on financial indexes*, Applied Economics Letters **29** (2022), 1880–1884.

[6] S. Hochreiter, *Long short-term memory*, Neural Computation MIT-Press, **9** (1997), 1735–1780.

[7] Y. Hong, W. Sun, B. Qianling and X. Mu, *SOM-BP neural network-based financial early-warning for listed companies*, Journal of Computational and Theoretical Nanoscience **13** (2016), 6860–6866.

[8] Z. Hua, Y. Wang, X. Xu, B. Zhang and L. Liang, *Predicting corporate financial distress based on integration of support vector machine and logistic regression*, Expert Systems with Applications **33** (2007), 434–440.

[9] S. B. Jabeur, *Bankruptcy prediction using partial least squares logistic regression*, Journal of Retailing and Consumer Services **36** (2017), 197–202.

[10] T. Korol, *Early warning models against bankruptcy risk for Central European and Latin American enterprises*, Economic Modelling **31** (2013), 22–30.

[11] S. Li and Y. Quan, *Financial risk prediction for listed companies using IPSO-BP neural network*, International Journal of Performability Engineering **15** (2019), 1209–1219.

[12] X. Li, J. Wang, and C. Yang, *Risk prediction in financial management of listed companies based on optimized BP neural network under digital economy*, Neural Computing and Applications **35** (2023), 2045–2058.

[13] B. Liu and W. Lu, *Surrogate models in machine learning for computational stochastic multiscale modelling in composite materials design*, International Journal of Hydromechatronics **5** (2022), 336–365.

[14] B. Liu, S. R. Penaka, W. Lu, K. Feng, A. Rebbling and T. Olofsson, *Data-driven quantitative analysis of an integrated open digital ecosystems platform for user-centric energy retrofits: A case study in northern sweden*, Technology in Society **75** (2023), 102347–102359.

[15] B. Liu, N. Vu-Bac, X. Zhuang, W. Lu, X. Fu and T. Rabczuk, *Al-DeMat: A web-based expert system platform for computationally expensive models in materials design*, Advances in Engineering Software **176** (2023): 103398.

[16] B. Liu, N. Vu-Bac, X. Zhuang, W. Lu, X. Fu and T. Rabczuk, *Al-DeMat: A web-based expert system platform for computationally expensive models in materials design*, Advances in Engineering Software **176** (2023), 103398–103418.

[17] B. Liu, Y. Wang, T. Rabczuk, T. Olofsson and W. Lu, *Multi-scale modeling in thermal conductivity of polyurethane incorporated with phase change materials using physics-informed neural networks*, Renewable Energy **220** (2024) 119565–119583.

[18] Z. Liu, G. Du, S. Zhou, H. Lu and H. Ji, *Analysis of internet financial risks based on deep learning and BP neural network*, Computational Economics **59** (2022), 1481–1499.

[19] J. A. Ohlson, *Financial ratios and the probabilistic prediction of bankruptcy*, Journal of Accounting Research **18** (1980), 109–131.

[20] A. Rostamian and J. G. O'Hara, *Event prediction within directional change framework using a CNN-LSTM model*, Neural Computing and Applications **34** (2022), 193–205.

[21] B. Sang, *Application of genetic algorithm and BP neural network in supply chain finance under information sharing*, Journal of Computational and Applied Mathematics **384** (2021), 113170–113180.

[22] L. C. Thomas, *A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers*, International Journal of Forecasting **16** (2000), 149–172.

[23] X. Yan, W. Weihan and M. Chang, *Research on financial assets transaction prediction model based on LSTM neural network*, Neural Computing and Applications **33** (2021), 257–270.

[24] X. Yin, J. Li, and S. Huang, *The improved genetic and BP hybrid algorithm and neural network economic early warning system*, Neural Computing and Applications **34** (2022), 3365–3374.

[25] Y. Zizi, M. Oudgou, and A. El Moudden, *Determinants and predictors of SMEs' financial failure: A logistic regression approach*, Risks **8** (2020), 107–127.

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S. Li
School of Finance and Economics, Zhejiang Industry Polytechnic College, shaoxing, Zhejiang, 312000, China
E-mail address: lisha810822@126.com

X. Chen
School of Information and Design, Zhejiang Industry Polytechnic College, shaoxing, Zhejiang, 312000, China
E-mail address: chenxuan1979@sina.com

T. Wang
Zhejiang Meike Optoelectronics Co., Ltd, Shaoxing, Zhejiang, 312000, China
E-mail address: wiseone@163.com