

# PSO-BP Neural Network Model in Stock Prediction

1<sup>st</sup> Beibei Wen

School of Information and Business Management  
Chengdu Neusoft University  
Chengdu, China  
wsndydxjq@163.com

2<sup>nd</sup> Yuanyuan Zhao

School of Information and Business Management  
Chengdu Neusoft University  
Chengdu, China  
danaiinl@163.com

**Abstract**—Stock prediction is crucial for financial product pricing, optimal asset allocation, speculative strategy research and risk management, etc., and there are many experts and scholars devoted to stock price prediction analysis. However, due to the volatility and non-linear nature of stock prices, it brings great difficulties to stock prediction, which makes some machine learning methods applied to stock prediction. This study introduces a Particle Swarm Optimization-Back Propagation (PSO-BP) neural network model designed to enhance stock price prediction. The PSO algorithm optimizes the BP neural network by fine-tuning the number of hidden layer nodes, thereby improving prediction accuracy and robustness. Experimental results reveal that the PSO-BP model not only reduces prediction time, averaging between 0.5 to 0.8 seconds, but also demonstrates a more efficient calculation speed compared to the traditional BP algorithm. The PSO-BP model performs better with increased sample data, showing minimal increases in calculation time, thus indicating its robust performance. The findings suggest that the PSO-BP model provides a reliable and efficient method for stock price prediction, with notable improvements in both speed and accuracy compared to existing methods.

**Keywords**—stock prediction, PSO algorithm, BP neural network model, hidden layer

## I. INTRODUCTION

With the acceleration of global economic integration, the stock market has become increasingly prominent in the global economy. However, in the stock market, there is a large amount of data, noise, and a high degree of non-linearity and instability. Stock price changes are affected by a variety of factors such as economy, policy, market and investor psychology, which makes stock price prediction very difficult. Intelligent analyses of the stock market can provide decision-making support to trading regulators, as well as bring benefits and risk avoidance to investors. This study aims to address these limitations by developing a robust and efficient model for handling non-linear and noisy data. Integrating Particle Swarm Optimization (PSO) with Backpropagation (BP) neural networks offers a promising solution, optimizing BP neural network parameters and structure to enhance performance.

Firstly, the introduction section highlights the importance and challenges of stock price prediction, setting the stage for the research. Following this, the related works section provides an overview of existing stock prediction models, emphasizing recent advancements and the relevance of PSO-BP neural networks. The methods section then describes the BP neural network and PSO algorithm, explaining their integration into the BP-PSO model. Subsequently, the results section presents the experimental findings, showcasing the model's performance and robustness. Finally, the discussion section summarizes the main discoveries, offers interpretations, discusses the impact, acknowledges limitations, and suggests future research directions.

## II. RELATED WORKS

Experts have long conducted specialized research on stock prediction models.

Kurani A combines ANN (artificial neural network) model with BP (Backpropagation) neural network to get better stock market prediction results. Also, Support Vector Machines have been used in stock market with good results, the prediction accuracy of a single Support Vector Machine is around 60-70% and the addition of Random Forest and Genetic Algorithms can make it better [1]. Milad Shahvaroughi Farahani used Artificial Neural Networks (ANN) and novel meta-heuristic algorithms to forecast the stock price index. He used Genetic Algorithm (GA) to screen the features from which the optimal and most relevant indexes were selected [2]. Zhang Y provides accurate prediction of US stock market volatility by analysing it. It was found that the volatility of the U.S. stock market can be predicted by integrating international volatility [3]. Vaziri J found that by modelling three types of stock market data based on fundamental, technical and time series data, the modified PSO-BiLSTM (particle swarm optimization-Bi-directional Long Short-Term Memory) algorithm has better predictive performance [4]. Meher B K used Autoregressive Integrated Moving Average model (ARIMA) model to predict the stocks of some pharmaceutical companies in the Indian BSE Composite 100 index [5]. The deep learning framework used by Anand C contains Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), Multilayer Perceptron (MLP), and Support Vector Machine (SVM) to predict stock prices using existing stock price information [6].

Hafis NURDIN obtained 84.55% correct rate by testing the graduation data of college students with artificial neural network method, and optimised it with particle swarm algorithm, and obtained 86.94% optimal solution [7]. Yiwen SHI collected the medical records of patients with mental illnesses, and used chaotic optimisation method to achieve the diagnosis and treatment of mental illnesses. On this basis, he used the neural network training technique to preprocess the clinical data of patients with mental illnesses that had been processed. He verified that the correct rate of this method in the diagnosis of mental diseases was over 95% through comparative experiments [8]. Sai XU combined particle swarm and neural network to construct a new tourism demand prediction model based on PSO-NN (Particle Swarm Optimization and Neural Network). Experiments show that the neural network based neural network prediction accuracy can reach 95.81%, which is about 10.09% higher than the conventional neural network model [9]. Zahra Shafiei Chafi and H. Afrakhte improved the prediction accuracy by precisely adjusting the parameters of the neural network [10].

### III. METHODS

#### A. Stock Prediction

The stock market is a matter of concern not only for the government, but also for investors. For investors, the more accurate they are in predicting the future, the more reliable their profits can be. From the perspective of a country, research on stock market forecasting is of great significance for China's economic development and financial construction. Therefore, studying the prediction of the stock market can better predict the stock market, reduce investment risks, and obtain maximum returns, which has very important theoretical and practical value. In order to predict changes in stock prices, there have been many stock analysis methods, such as technical analysis (moving average method, trading volume chart method) and psychological analysis (herd behavior in the stock market). However, neural networks can transform input-output problems into a nonlinear function, which means achieving nonlinear mapping between  $n$  input spaces and  $m$  output spaces, thus better handling nonlinear problems [11].

#### B. BP Neural Network Model

BPNN utilizes error backpropagation algorithm for continuous learning. It is a commonly used neural network model and has important applications in network detection,

information prediction, and other fields. The basic idea of this method is to use LMS (Least Mean Square) learning algorithm, introduce loss function and various optimization methods to update the weights and thresholds of the network, so as to minimize the deviation between the neural network output and the actual value. The general structure of neural network is as shown in Figure 1 [12].

#### C. PSO Algorithm

PSO is an evolutionary computing technique based on group predation behavior, which has been proven to be an effective method for solving optimal problems in recent years. The particle swarm optimization algorithm can be like an abstract situation where there is a piece of food in one place, and many birds can search for it in different places. Birds have no idea where their food is, all they can do is search for the approximate distance between them and their prey and the transmission of information between them. PSO algorithm is inspired by this model and used to solve optimization problems. Each solution set of a particle swarm is called a "particle". The particle moves along a specific path and velocity throughout the search space based on its own velocity and the relationships between other particles. Birds can be abstracted as particles (points) without mass or volume, and extended to the  $D$  dimension.

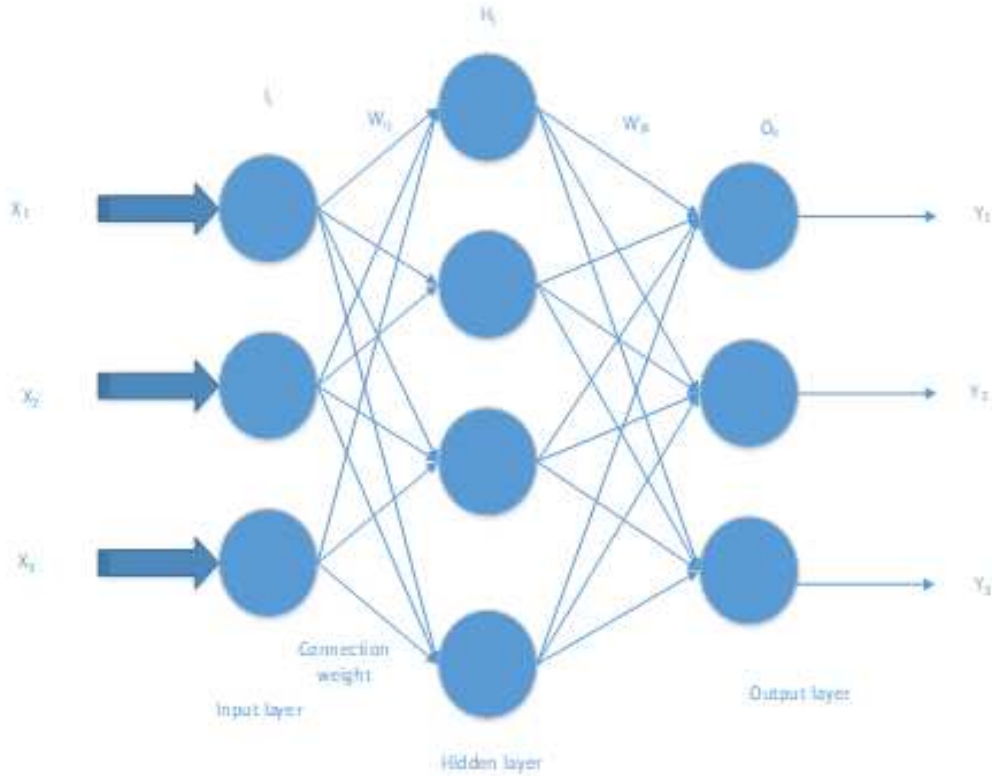


Fig. 1. Topological structure of BP neural network

#### D. Stock Prediction Model on BP-PSO Algorithm

BP neural network is a gradient dimensionality reduction algorithm based on error function. Essentially, it is a local optimization algorithm that suffers from slow convergence, susceptibility to local minima, initial weights, learning rate, and other factors. PSO is a population intelligence algorithm that can adjust the position, velocity, and other information of the particle swarm to achieve global optimization, with fast convergence speed and strong robustness. PSO-BP neural

network combines PSO algorithm with BPNN organically, overcoming the shortcomings of traditional BP network, such as slow convergence speed and easy falling into local minima. The basic idea of PSO-BP neural network is to combine the error propagation training of PSO algorithm and BPNN, using error as the fitness function. This article iteratively optimizes the weights and thresholds of the BPNN to obtain initial weights and thresholds with high adaptability, and applies them to the BPNN to ultimately obtain values that meet the

accuracy requirements. It was modeled using PSO-BP neural network. The process is as follows:

Step 1: Initialize particle  $X_i = (x_{i1}, x_{i2})$  and velocity  $V_i = (v_{i1}, v_{i2})$ , obtain the initial number of input layer nodes  $p$  and hidden layer nodes  $L(p = x_{i1}, L = x_{i2})$  of the neural network, and further convert the high-frequency sequence  $c_v''$  into temporal data:

$$T_v'' = \{\vec{E}_i, \vec{O}_i, \mu(t_i) | i = p + 1, P + 2, \dots, I\} \quad (1)$$

Step 2: Initialize a new neural network, including initializing the learning rate  $\eta$  for weights and thresholds, selecting training and transfer functions.

Step 3: Import temporal data  $T_v''$  into the neural network model for training.

Step 4: Through the previous step, obtain the training error  $w$  under the initial neural structure, which serves as the initial fitness value for PSO optimization.

Step 5: Repeat

- Update particle velocity and position: Obtain new input node numbers  $p$  and hidden layer node numbers  $L$ , and convert sequence  $c_v''$  into new temporal data  $T_v''$  based on their values.
- Based on the  $P$  and  $L$  values obtained in the previous step, initialize the new neural network, including weight and threshold initialization, learning rate  $\eta$ , selection of training function and transfer function[13].

After updating the velocity and position of particles, new input nodes and hidden layer nodes can be obtained. The structure of the new neural network is defined, and the training process of the new neural network is defined as the process of calculating the moderation function. The training error (average absolute error) is the moderation value, and then the individual extremum and population extremum are updated based on the particle's moderation value, iterating until a certain number of iterations are reached. The above introduces the optimization process of PSO algorithm, and the specific process of generating a neural network structure corresponding to a set of high-frequency sequences is introduced next.

#### E. Network Structure Parameter Design

Usually only two implicit layers are needed to satisfy the need to construct a mathematical model. The neural network algorithm is so overpowered for data training that the algorithm is extremely susceptible to overfitting. A large number of hidden layer nodes not only improve the training speed of the network, but also retain irregular information in the data, such as interference, noise, etc., which affects the network's generalization performance. The commonly used testing methods are:

First, the empirical formula is used to determine:

$$m = \sqrt{n + L} - a \quad \text{Or} \quad m = \sqrt{nL} \quad (2)$$

Change  $m$  and compare the error values of the training set by not adjusting the parameters too much, in order to seek the optimal parameter values

In this example, the experiment selected a hidden layer of 10 based on the aforementioned empirical rule. In addition, the fitting accuracy of this network is set to 0.001, and the number of learning iterations is set to 10000.

### IV. RESULTS AND DISCUSSION

#### A. Experimental Data Sources

This article selects 4000 trading day data from January 1, 2020 to December 31, 2021 of the Shanghai Composite Index as the model data source, dividing training and prediction data into adjacent ones. It conducts experiments on training 3000 data, predicting 500 data, training 1000 data, and predicting 500 data. After this article, the mean square error, accuracy of trend direction, and calculation time of different algorithms were calculated using data from 1000 to 5000. The results are shown below.

To demonstrate the universality of the model, this section predicts stock prices and stock indices separately. The stock data selected the stock price data of four companies, Yunda Group (002120), Manbuzhe (002351), Penghui Energy (300438), and Jianfan Biotechnology (300529). The selected time range for the dataset is from January 1, 2020 to December 31, 2021, and each stock contains 2410 stock price data. The sample data example is shown in Table 1 (from January 1, 2020 to January 31, 2020).

TABLE I. SAMPLE DATA EXAMPLE(YUNDA GROUP)

Date	Open	High	Low	Close	Adj Close	Volume
1/2	25.76154	25.76923	24.73077	25.33077	24.83453	16893866
1/3	24.94615	25.57692	24.86154	24.94615	24.45745	9105409
1/6	24.94615	25.63846	24.52308	25.36923	24.87224	13188747
1/7	25.11538	25.44615	24.7	25	24.51024	15527367
1/8	24.97692	25.19231	24.64615	24.77692	24.29153	9273316
1/9	25.06923	25.3	24.59231	24.78462	24.29907	11531959
1/10	24.86923	24.91538	24.19231	24.26923	23.79379	9694122
1/13	24.43846	24.66923	24.13077	24.59231	24.11053	11840838
1/14	24.82308	25.29231	24.28462	24.4	23.922	12886302
1/15	24.40769	24.68461	23.84615	23.90769	23.43933	10740680
1/16	23.96154	24.01539	23.39231	23.42308	22.96421	8332586
1/17	23.46154	23.82308	23.28462	23.40769	22.94913	11147077
1/20	23.47692	25.07692	23.47692	24.84615	24.35941	19662427
1/21	25.15385	25.53846	24.26923	24.87692	24.38957	19247952
1/22	24.87692	25.24615	23.69231	23.95385	23.48458	19135274
1/23	23.69231	24.26923	22.47692	22.81538	22.36842	15628176

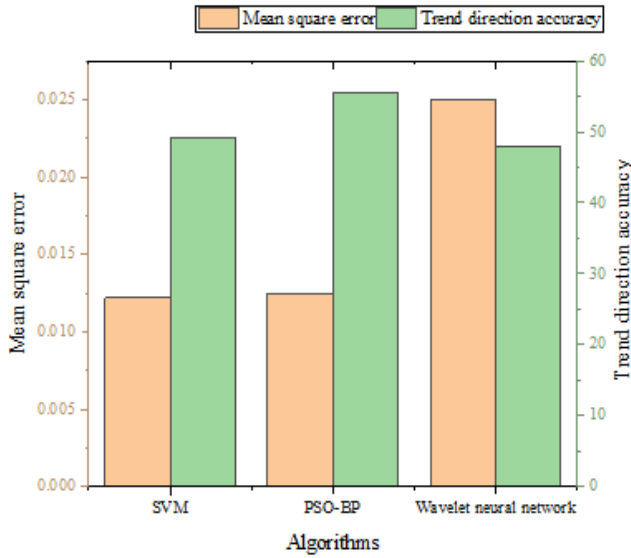


Fig. 2. Results with 1000 training data

### B. Results

From Figure 2, it can be seen that when the training data is 1000, the mean square error of the stock prediction models using SVM (support vector machines), PSO-BP algorithm, and wavelet neural network algorithm is below 0.025. The accuracy of predicting the upward trend of stocks is below 60%, indicating that the accuracy of prediction based on PSO-BP algorithm is higher than other models.

As shown in Figure 3, when the number of training data increases to 3000, the mean square error of the PSO-BP algorithm model decreases significantly compared to Figure 2. The accuracy of the three models has slightly changed but not significantly. From Figure 3, it can still be seen that the mean square error based on PSO-BP algorithm is small, and the accuracy of predicting stock trend direction is high, so the algorithm in this article is the best.



Fig. 3. Results with 3000 training data

From Figure 4, it can be seen that the stock prediction model of the PSO-BP algorithm is close to the actual data results in predicting the closing price of stocks. This indicates

that the PSO-BP algorithm can predict the closing price of stocks within a certain error range based on relevant variables[14].

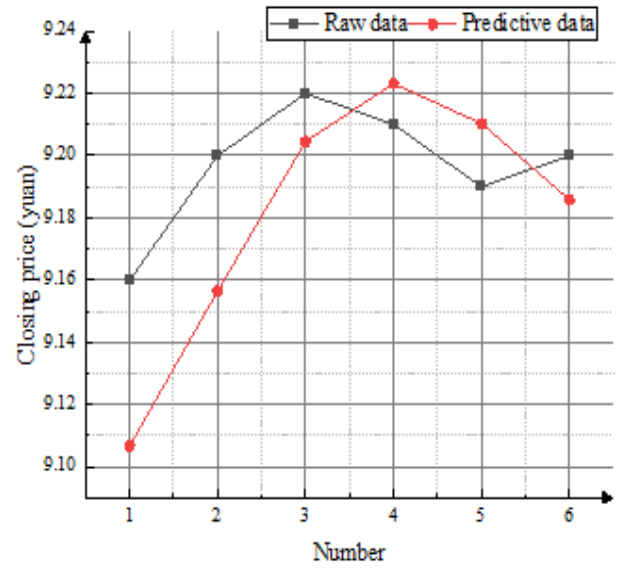


Fig. 4. Partial Forecast Closing Price Result Data

TABLE II. ALGORITHM CALCULATION TIME (S)

Sample data	BP	PSO-BP
1000	1	0.5
2000	1.5	0.7
3000	2.1	0.71
4000	3	0.72
5000	3.5	0.8

Table 2 demonstrates that the PSO-BP algorithm's rise in computation time with increasing sample data is comparatively minor, demonstrating the algorithm's high robustness.

### C. Discussion

The main conclusions show that the PSO-BP model outperforms traditional BP neural networks and SVMs in terms of prediction accuracy and computational speed, especially when dealing with larger datasets exhibiting lower mean square error and better trend prediction. By enhancing the weights and thresholds through Particle Swarm Optimisation (PSO), the model improves the convergence speed and accuracy, and effectively overcomes the convergence and local minima problems for large-scale stock prediction. However, the evaluation of the model is currently limited to specific stocks and periods, which may result in higher computational costs and require more adjustments. To address these issues, it is recommended that the model be tested using different datasets and longer time frames, and that further optimisation and integration with techniques such as deep learning be considered to improve performance.

## V. CONCLUSIONS

Stock prediction is crucial for financial product pricing, optimal asset allocation, speculative strategy research and risk management, etc., and there are many experts and scholars devoted to stock price prediction analysis. However, due to the volatility and non-linear nature of stock prices, it brings great difficulties to stock prediction, which makes some machine learning methods applied to stock prediction. This

article is based on this and explores the construction scheme of prediction models. The stock prediction model based on PSO-BP algorithm has many advantages, which can effectively improve the accuracy and robustness of stock price prediction. With the continuous development and changes of financial markets, the PSO-BP algorithm can become an important research direction in the field of stock prediction, providing more reliable decision-making basis for investors and analysts.

Furthermore, investigating hybrid strategies that combine the PSO-BP model with cutting-edge methodologies like ensemble methods or deep learning may be able to predict stock prices with even higher robustness and accuracy.

This paper is a phased research result of the smart tax ecosystem under the 2022 annual project data-based tax governance of Sichuan Provincial Key Research Base of Philosophy and Social Sciences (Regional Public Management Informatization Research Center)--Taking Chengdu Tax Bureau as an Example (Project No. OGXH22-02).

#### AUTHOR CONTRIBUTIONS

The corresponding author is Yuanyuan Zhao

#### REFERENCES

- [1] Kurani A, Doshi P, Vakharia A. A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting[J]. *Annals of Data Science*, 2023, 10(1): 183-208.
- [2] Milad Shahvaroughi Farahani , Seyed Hossein Razavi Hajiagha. Forecasting stock price using integrated artificial neural network and metaheuristic algorithms compared to time series models[J]. *Soft computing*, 2021, 25(13): 8483-8513.
- [3] Zhang Y, Wang Y, Ma F. Forecasting US stock market volatility: How to use international volatility information[J]. *Journal of Forecasting*, 2021, 40(5): 733-768.
- [4] Vaziri J , Farid D , Ardakani M N ,et al.A time-varying stock portfolio selection model based on optimized PSO-BiLSTM and multi-objective mathematical programming under budget constraints[J].*Neural Computing and Applications*, 2023, 35(25):18445-18470.
- [5] Meher B K, Hawaldar I T, Spulbar C M.Forecasting stock market prices using mixed ARIMA model: A case study of Indian pharmaceutical companies[J]. *Investment Management and Financial Innovations*, 2021, 18(1): 42-54.
- [6] Anand C .Comparison of Stock Price Prediction Models using Pre-trained Neural Networks[J].*Journal of Ubiquitous Computing and Communication Technologies*, 2021, 3(2):122-134.
- [7] Hafis NURDIN, SARTINI, SUMARNA ,et al.Prediction of Student Graduation with the Neural Network Method Based on Particle Swarm Optimization[J]. *sinkron*, 2023, 10(7):2353-2362.
- [8] Yiwen SHI, Zihan WANG, Yifan ZHAO. Prediction algorithm of improved neural network psychological disorder information system based on particle swarm optimization[J]. *2022 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA)*, 2022,10(7):1109-1120.
- [9] Sai XU, Shuxia WANG. Tourism Demand Prediction Model Using Particle Swarm Algorithm and Neural Network in Big Data Environment[J]. *Journal of Environmental and Public Health*, 2022,9(12):1-10.
- [10] Zahra Shafiei CHAFI, H. AFRAKHTE. Short-Term Load Forecasting Using Neural Network and Particle Swarm Optimization (PSO) Algorithm[J]. *Mathematical Problems in Engineering*, 2021,11(05):1155-1164.
- [11] Salisu A A, Ogbonna A E, Adediran I. Stock - induced Google trends and the predictability of sectoral stock returns[J]. *Journal of Forecasting*, 2020, 40(2): 327-345.
- [12] Satpathy, R.B. and GP, R., 2024. Conformal eight - port dual band antenna with switchable radiation pattern for 5G enabled on - body wireless communications. *Microwave and Optical Technology Letters*, 66(1), p.e33910.
- [13] Mazlan A U , Sahabudin N A , Remli M A ,et al.A Review on Recent Progress in Machine Learning and Deep Learning Methods for Cancer Classification on Gene Expression Data[J].*Processes*, 2021, 9(8):1466-1468.
- [14] Rouf N , Rouf N , Malik M B ,et al.Stock Market Prediction Using Machine Learning Techniques: A Decade Survey on Methodologies, Recent Developments, and Future Directions[J].*Electronics*, 2021, 10(21):2717-2719.