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# Stock Price Forecasting Based on Quantum Particle Swarm

# Optimization

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**ABSTRACT:** The stock market is very volatile, so the change of the stock price is also widely concerned by investors. In this paper, a new stock price forecasting model based on Quantum Particle Swarm Optimization(QPSO), Quantum Bee Colony Optimization Algorithm(QABC) and Quantum Fruit Fly Optimization Algorithm (QFOA) is proposed. The three methods all use BP neural network to adjust the parameters of particle swarm, bee colony and Drosophila to reach the optimal parameters. Taking the daily closing price of CITIC Securities and Tianfeng Securities, a large-scale and a small-scale securities company, as the object of empirical analysis, comparing the accuracy of the three methods in predicting stocks, it also analyzes whether the size of the company has an effect on the accuracy of the model. The results show that the prediction effect of qpso is the best, and the size of the company has some influence on the prediction effect.

KEYWORDS: Quantum Particle Swarm Optimization Algorithm, SVR Neural Network ,stock prediction

# 1. INTRODUCTION

For a long time, the prediction of the stock price has been a hot topic in finance, so when studying the stock prediction, the former scholars established a lot of prediction models, and the latter scholars basically improved the models on the basis of the former scholars, or to add innovative elements to the original model, so that the model has higher accuracy. But the models used in the prediction are basically the same as those used before. The method used in this paper is a method that has not been used in stock prediction before, so this paper mainly verifies the Quantum Particle Swarm Optimization Algorithm (QPSO), Quantum Bee Colony Optimization Algorithm(QABC) and Quantum Fruit Fly Optimization Algorithm (QFOA) were used to determine whether the models could predict stocks well and choose the best model.

Most people usually use linear forecasting models including ARIMA model, GARCH model and EGARCH model, and nonlinear forecasting models including BP Neural Network and LSTM model .So let's take a brief look at what we've learned so far:Ge Zhiyuan et al.(2016)<sup>[1]</sup> constructed an adaptive model of time series based on genetic programming, which combined the genetic programming method and time series effectively, the results show that the prediction accuracy of the improved genetic programming method is higher, and the relationship between input and output can be expressed more intuitively. Using BP Neural Network (BPNN) and Support vector machine regression (SVR) ,Ran Yangfan et al.(2017)<sup>[2]</sup> combined emotion analysis and machine learning to obtain a more targeted prediction model. In order to solve the problems of low accuracy and time-consuming in training traditional neural networks due to the huge data, a prediction method based on Pearson feature selection and XGBOOST algorithm was proposed.<sup>[3]</sup> The results show that the use of feature refinement method can effectively improve the forecasting effect by retaining the 4 most relevant attributes, and it is more practical to simplify the analytical thinking in the analysis of stock price trend. In order to find the best stock, Wang Yan et al.(2019)<sup>[4]</sup> optimized the parameters of XGBoost model by grid search algorithm, and built gs-XGBoost financial forecast model, and applied it to short-term stock forecast. The results show that GS-XGBoost model has better prediction results in MSE, RMSE and Mae, and has better fitting performance in short-term stock forecasting. Jin Jianhai et al. (2020)<sup>[5]</sup> aim at the problems of low efficiency, slow convergence speed and easy to fall into local optimum in the current



mainstream route planning algorithm of unmanned craft, in this paper, a quantum Particle swarm optimization algorithm with strong global search ability is used to solve the optimal route planning of unmanned aerial vehicles (uavs). The results show that the method has strong searching ability, fast convergence speed and good stability, and can be applied to the route planning of unmanned craft in different environments. Shi Jiannan et al. (2020)<sup>[6]</sup> address the problems of difficult effective feature extraction and low precision of price forecasting caused by complex stock market relations, in this paper, a time series forecasting method of stock price based on dynamic mode decomposition (DMD-LSTM) is proposed. The experimental results on Angang stock (SH000898) show that this method can achieve higher precision of price forecasting and more accurately describe the change law of stock price than the traditional forecasting method under the specific market background. Ding Wenjuan (2021)<sup>[7]</sup> predicts the precision and effect of the stock price of LSTM neural network model and Arima model by error index and trading performance. The result shows that the depth neural network model of LSTM model has better prediction precision. Zhang Yumeng et al. (2021)<sup>[8]</sup> used BP neural network and ARMA-GARCH model to forecast the closing price of SAIC, and compared the forecast results. The results show that BP neural network is more accurate in long-term forecasting, a RMA-GARCH model has a slight advantage in short-term forecasting.Hu Yuwen (2021)<sup>[9]</sup>used the data of five kinds of technical indexes to reduce the dimension of indexes by PCA and Lasso, then used the LSTM model to predict the stock of ping an bank, and compared the stability and accuracy of LASSO-LSTM model and LSTM model, the results show that PCA-LSTM model can greatly reduce data redundancy and obtain higher prediction accuracy. Xu Yuemei et al. (2021)<sup>[10]</sup> in order to improve the accuracy of stock forecasting, the convolutional neural network and two-way longterm and short-term memory models are introduced, by extracting the types of news events and the tendency of news emotion in financial news, the stock forecasting model of financial data, news event features and news emotion features in stock market is obtained, the introduction of news event type and emotional tendency can improve the performance of stock trend prediction.

Particle swarm optimization algorithms are rarely used to predict stocks, but are mostly used in computer applications, digital engineering, and design, so they are rarely used in the neighborhood of stock forecasting, so this gives us an innovation. The following are the main areas covered by the Particle swarm optimization: In order to solve the problem of weapon target assignment, Liu Kun et al.(2016)<sup>[11]</sup> proposed a kind of quantum Particle swarm optimization with ranking mapping. Simulation results show that the algorithm has high convergence speed and stability, and can effectively solve the problem of target assignment questions. Zhao Ji et al.(2017)<sup>[12]</sup> proposed a Non-revisited quantum behavior Particle swarm optimization (NrQPSO) based on evolutionary search information to solve the problem that the quantum behavior Particle swarm optimization might converge too early and fall into local optimum. Compared with other traditional algorithms, this algorithm has better optimization performance. An improved algorithm for optimizing the branch of quantum Particle swarm optimization is proposed in this paper. The method of parameters of SVM can improve the speed and accuracy of the solution of support vector machine.<sup>[13]</sup>Tang Rui et al.(2019)<sup>[14]</sup> proposed a phase space based GQPSO-WNN hybrid prediction model based on the chaos and predictability of Quantitative analysis traffic flow, which can predict traffic flow more accurately. Tan Zhongfu et al. (2020)<sup>[15]</sup> used the coevolutionary immune quantum partical swarm optimization(CIOPSO) to search for the optimal solution, in order to improve the economic benefit of EV participating in the virtual power plant, and the balance between supply and demand in the virtual power plant. Li Fei et al.(2021)<sup>[16]</sup> to solve the difficult problem of high dimensional multiobjective optimization, a high dimensional multiobjective Particle swarm optimization (R2-MOPSO-II) based on R2 index and Target space decomposition is proposed. The results show that the proposed algorithm has better convergence and diversity in solving DTLZ and WFG test problems. Zhang Yu et al. (2021)<sup>[17]</sup> adaptive adjustment of inertia weight and learning factor based on particle swarm optimization (PSO) by using the idea of inversion of measured evaporation duct profile parameters from radar sea clutter power and evaporation duct model, adaptive compression factor is introduced. The results show that the improved Particle swarm optimization has better global convergence, and the inversion speed is obviously improved when the data are processed on a large scale. In order to solve the problems of unbalanced load and wasted bandwidth resource in data center network, Ma Shuqing et al. (2021)<sup>[18]</sup> proposed a traffic scheduling strategy based on Particle swarm optimization, this algorithm effectively improves the average throughput of the network, reduces the waste of resources, and achieves better load balance. Zhang Qian (2021)<sup>[19]</sup> in order to predict the network security situation in a period of time in the future, a neural network model based on Particle swarm optimization is proposed. The results show that the optimized model is feasible and the prediction accuracy is improved significantly.

Compared with the existing research, the main features of this paper are as follows:

(1)Innovation of research methods, the use of particle swarm optimization algorithm for stock forecasting.

(2)Comparing the fitting degree of the three methods, it is found that the quantum optimized particle swarm is the best one.

(3)Stock forecast reference indicators, most of the stock reference indicators for the KDJ and MACD, this article in addition to these four indicators, but also added OBV, MFI and PSY indicators.

#### 2. RESEARCH METHODS

#### 2.1 Quantum Optimization Particle Swarm Optimization (QPSO)

Quantum coding is used to optimize the particle swarm optimization program: first, the parameters of the Quantum Optimization Particle Swarm Optimization need to be established, which is easy to calculate. Secondly, the address of the particle swarm is initialized. The third step is to describe the particle case by using the wave function f(x, b), since the velocity and position of each particle change with each iteration depending on its momentum and optimal position.<sup>[20]</sup>In the fourth step, in order to obtain the probability density function of randomly occurring particles in space, the Schrödinger equation is processed to produce a result. Step 5, in order to get the particle's address equation, use the Monte Carlo method, no conditions, random imitation. Here's the equation for taking Monte Carlo method and mimicking the situation to get the particle:

$$x(b) = P \pm \frac{L}{2} \ln\left(\frac{1}{u}\right)$$

In this formula, u-is an arbitrary number which follows an average distribution on [0,1]. Where  $l (B + 1) = 2\beta$  something mbest-X (b) | has been defined. The equation used to calculate the Quantum Optimization Particle Swarm Optimization is:

mbest = 
$$\frac{1}{N} \sum_{i=1}^{N} P_i = (\frac{1}{N} \sum_{i=1}^{N} P_{i1} \dots \frac{1}{N} \sum_{i=1}^{N} P_{iD})$$
  
 $P_{id} = \eta * P_{id} + (1 - \eta) * P_{gd}$ 

#### 2.2 Quantum Optimized Bee Colony Algorithm (QABC)

When Bee Colony algorithm is optimized by quantum coding, the location dimension of bee is represented by 3L \* 2. In SVR model, 3 represents its three parameters, 1 is the number of bits that each parameter needs to be converted into binary coding, and 2 is the two different aspects of quantum gate, the dimensions of the bee's position are within the limits of the coordinates of [0,1]. (1)The original position of bees: the original position of bees was selected randomly.

(2)The hiring process: if one bee forager corresponds to one source of honey, the bee forager corresponding to the first source of honey will search for a new source of honey according to the following formula:

$$\dot{M}_{id} = M_{id} + \phi_{id} (M_{id} - M_{kd})$$

(3) The possible solutions arising from the selected wait-and-see process:

$$M_{i}^{'} = \{M_{i}^{'}, M_{i}^{'}, \dots, M_{iD}^{'}\}$$

(4) The original explanation:

$$M_{i} = \{M_{i1}, M_{i2}, \dots, M_{iD}\}$$

Compared with the original solution, the regenerated potential solution uses greedy selection strategy to leave a better solution. For each observed bee, the selection of a corresponding honey source is based on probability, and the formula is:

$$P_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j}$$

Where the fitness  $M_i$  of the possible solution is fit<sub>i</sub>. The observed bees were able to search for new possible solutions according to the above probability formula.

(5) Reconnaissance process: when all the observed bees and honeybees have searched the whole searchable space, if they fail to

increase the fitness of a source within a given step (defined as the control parameter "limit"), the source should be discarded, then the foraging bees are transformed into scouts, and the Scouts search for new possible solutions through the following formula:

$$M_{id} = M_d^{\min} + r(M_d^{\max} - M_d^{\min})$$

(6) To measure the coding position of the Bee: in quantum computing, the fundamental states of two kinds of tiny particles are represented by qubits  $|0\rangle$  and  $|1\rangle$ . According to the superposition principle, the linear combination of the two basic states is the superposition state of quantum information, that is,  $|\psi\rangle = \alpha |0\rangle + \beta |1\rangle$ ,  $\alpha$  and  $\beta$  in the equation are complex numbers and also represent the probability amplitudes of qubit states, that is, the probability that the qubit states  $|\psi\rangle$  are shrunk to  $|0\rangle$  and  $|1\rangle$ . States due to the measurement, respectively, and the normalization conditions are met.

When we measure a Quantum Optimized Bee Colony Algorithm, we encode the probability amplitude of the qubit. The scheme is as follows:

$$P_{i} = \left[ \left| \frac{\cos(\theta_{i1})}{\sin(\theta_{i1})} \right| \left| \frac{\cos(\theta_{i2})}{\sin(\theta_{i2})} \right| \frac{\Lambda}{\Lambda} \left| \frac{\cos(\theta_{ik})}{\sin(\theta_{ik})} \right| \right]_{\theta_{ij}} = 2\pi \times RAND, i = 1, 2, \dots, j = 1, 2, \dots, k$$

" $\theta$ " is the phase of the qubit, "n" is the number of fruit flies, "k "is the number of qubits, which is the dimension of the solution space, and "RAND" is a random number, but it is limited to [0,1]. The two lines are the forms of each qubit, which correspond to the probability amplitudes of the two quantum fundamental states, and also satisfy the normalization conditions. Therefore, the two cultural coding chains exist in each individual, the candidate solution of the optimization problem contains every coding chain. It is obvious that the number of candidate solutions obtained by Quantum Particle Swarm Optimization is twice as large as that by Particle Swarm Optimization with the same population size, which improves the diversity of solution space and the success probability of finding the optimal solution.

To measure the bee's code, we square each digit of the Bee's code  $Q_i$ , to get its binary code:

$$Z_{id} = \begin{cases} 1, & \text{if}(Q_{id})^2 < RAND \\ 0, & \text{if}(Q_{id})^2 \ge RAND \end{cases}$$

To get its binary code.

(7) Decision variables obtained from binary conversion to decimal encoding: that is, the binary encoding of each decision variable is converted to obtain the decimal value of the required decision variable.

(8) Quantum revolving gate: in order to change the quantum bit phase, we use the quantum revolving gate to update the probability amplitude of the quantum bit, so that the Drosophila code produces the mutation effect.

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \cos_{\theta_i} - \sin_{\theta_i} \\ \sin_{\theta_i} & \cos_{\theta_i} \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix}$$

#### 2.3 Quantum Optimized Fruit Fly Optimization Algorithm (QFOA)

When the Fruit Fly Optimization Algorithm is optimized by quantum coding, the position dimension of Drosophila is represented by 3L \* 2. In SVR model, 3 represents its three parameters, 1 is the number of bits that each parameter needs to be converted into binary coding, and 2 is the two different aspects of quantum gate, the dimensions of the Drosophila position are within the interval limits of [0,1].

(1)The original state of the Drosophila position: a randomly selected Drosophila position q0 was selected within the whole range of the definition, and the popsize positions appeared randomly through the action of uniform distribution.

(2)Transfer: select the best Drosophila site q, q0 = q.

(3)Scatter: take Q0 as the center point, and again distribute it evenly to randomly generate additional popsize locations.

(4)Measure the coding position of Drosophila.

The fundamental states of two kinds of small particles are represented by qubit  $|0\rangle$  and  $|1\rangle$  in the quantum rotating gate. According to the superposition principle, the linear combination of the two basic states is the superposition state of quantum information, that

is  $|\psi = \alpha | 0\rangle + \beta | 1\rangle$ , the  $\alpha$  and  $\beta$  in the equation are complex numbers and also represent the probability amplitudes of the qubit states, i. e. the probability that the qubit state  $|\psi\rangle$  is shrunk to  $|0\rangle$  and  $|1\rangle$  States due to the measurement, respectively, and the normalization conditions are met.

In the Quantum Optimized Fruit Fly Optimization Algorithm, the probability amplitude of qubits is used to encode Drosophila. The scheme is as follows:

$$P_{i} = \left[ \left| \frac{\cos(\theta_{i1})}{\sin(\theta_{i2})} \right| \left| \frac{\cos(\theta_{i2})}{\sin(\theta_{i2})} \right| \frac{\Lambda}{\Lambda} \left| \frac{\cos(\theta_{ik})}{\sin(\theta_{ik})} \right| \right] \theta_{ij} = 2\pi \times RAND, i = 1, 2, \dots, j = 1, 2, \dots, k$$

" $\theta$ " is the phase of the qubit, "n" is the number of fruit flies, "k" is the number of qubits, which is the dimension of the solution space, and "RAND" is a random number, but it is limited to [0,1]. The two lines are the forms of each qubit, which correspond to the probability amplitudes of the two quantum fundamental states, and also satisfy the normalization conditions. Therefore, the two cultural coding chains exist in each individual, the candidate solution of the optimization problem contains every coding chain. Obviously, under the condition of constant population size, Quantum optimized Fruit Fly Optimization Algorithm can get twice as many candidate solutions as Fruit Fly Optimization Algorithm, which improves the diversity of solution space and the success probability of finding the optimal solution.

When measuring fly coding, we calculate the square of each digit encoded by the fly population  $Q_i$ :

$$\mathbf{Z}_{id} = \begin{cases} 1, & \text{if}(\mathbf{Q}_{id})^2 < RAND \\ 0, & \text{if}(\mathbf{Q}_{id})^2 \ge RAND \end{cases}$$

The binary encoding  $Z_i$  is obtained.

(5)Decision variables obtained from binary conversion to decimal encoding: that is, the binary encoding of each decision variable is converted to obtain the decimal value of the required decision variable.(6)Calculation of objective function value: the calculation of the objective function for the position of Drosophila.

(6)Calculate the objective function: calculate the position of Drosophila melanogaster.

(7)Quantum Revolving Gate: in order to change the quantum bit phase, we use the quantum revolving gate to update the probability amplitude of the quantum bit, so that the Drosophila code produces the mutation effect:

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \cos_{\theta_i} - \sin_{\theta_i} \\ \sin_{\theta_i} & \cos_{\theta_i} \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix}$$

#### 3. EMPIRICAL ANALYSIS

#### 3.1 Data and models

This article is based on 345 transactions of CITIC Securities and tianfeng securities from Feb. 17,2020, to July 15,2020, in Netease Finance and economics. The data are based on the changes in the stock prices of 2021 securities from Feb. 17,2020 to July 15,2020.By calculating the daily closing price, daily opening price, daily trading volume, daily maximum price and daily minimum price, seven variables are needed: KDJ Index, OBV Index, MFI Index, PSY Index and MACD Index. The calculated 345 groups of data were divided into five groups and subrogated into three models (QPSO, QABC and QFOA) to cross-validate them. The first four groups were trained to predict the stock prices of the fifth group, finally, the predicted stock price is compared with the actual stock price. The higher the consistency of the model, the better the prediction effect of the improved model is. The following table 1 and table 2 provide narrative statistics for the two companies:

#### Table 1. Narrative statistics of CITIC Securities

	K%	D%	J%	OBV	MFI	PSY	MACD
N	345	345	345	345	345	345	345
MAX	10.00	9.80	1.65	6.03	9.55	9.17	2.52

MIN	0.00	0.06	-0.78	2.00	0.78	2.50	-1.32	
AVG	4.35	4.36	0.43	3.34	5.22	5.83	0.02	
STD	2.73	2.52	0.42	0.68	1.72	1.24	0.62	

Table 2 narrative statistics of Tianfeng Securities

	K%	D%	J%	OBV	MFI	PSY	MACD
N	345	345	345	345	345	345	345
MAX	10.00	9.57	1.89	1.23	8.82	8.33	0.58
MIN	0.00	0.00	-0.73	0.45	1.10	2.50	-1.73
AVG	3.95	3.97	0.39	1.00	5.27	5.38	-0.03
STD	2.82	2.60	0.44	0.17	1.48	1.27	0.24

**3.2 A graphic comparison of the actual and forecast value of CITIC Securities:** 



Figure 1: a graphic comparison between the actual value of CITIC Securities' share price and the predicted value of QPSO







Figure 3: A graphic comparison between the actual value of citic securities share price and the predicted value of QFOA

3.3 Graphic comparison of actual and forecast value of tianfeng securities:



Figure 4: a graphical comparison between the actual value of tianfeng securities and the predicted value of QPSO



Figure 5: a graphic comparison between the actual value of Tianfeng's stock price and the predicted value of QABC



Figure 6: a graphic comparison between the actual value of tianfeng securities and the predicted value of QFOA

From the coincidence of the curves shown in figure, two curves are observed between the actual values and the predicted values of qpso-svm, whether it is the larger citic securities, or the smaller tianfeng securities, quantum particle swarm is the best fit. For QABC and QFOA, these two models are less effective than QPSO. Through the comparison of the above figures, it can be found that the forecast effect of CITIC Securities using these three models is better than that of tianfeng securities. Therefore, this shows that the size of the stock will have a certain impact on the forecast, but it won't make much difference.

	Index	QPSO	QABC	QFOA
	R2	0.983	0.908	0.965
	MSE	0.166	5.093	0.735
<b>CITIC Securities</b>	RMSE	0.407	2.256	0.857
	MAPE	1.297	7.995	2.845
	MAD	0.315	1.913	0.703

Table 3. Comparison results of CITIC Securities model data

#### Table 4. Comparison results of tianfeng securities model data

	Index	QPSO	QABC	QFOA
	R2	0.964	0.971	0.909
tion for a	MSE	0.335	0.019	0.327
	RMSE	0.579	0.139	0.572
securities	MAPE	3.111	2.378	8.164
	MAD	0.501	0.116	0.516

Figures 1 to 6 show an intuitive analysis of the stocks, while tables 3 and 4 show an objective analysis of the two stocks. From Table 3, the data from the three models of CITIC Securities are compared, it can be seen that the R2(decisive coefficient) of quantum particle swarm is 0.983, and the higher the decisive coefficient is, that is, the closer to 1, the better the fitting effect is. In general, R2 greater than 0.8 indicates that the model fits well, so QPSO, QABC and QFOA fit well, but QPSO fits best. The MSE (mean square error) of the QPSO is 0.166, which is less than the other two models, and MSE is generally less than 2 which is a reasonable range. Less than 2 means that the change of the data is less, and the prediction model describes the experimental data with better accuracy, the smaller the value of MSE, the higher the accuracy. RMSE (root mean square error) is the deviation between the real value and the predicted value, so the smaller the RMSE value is, the better. In the three models, the RMSE value of the QPSO is the smallest, so the deviation between the actual value and the predicted value of the QPSO is the smallest. MAPE (mean percentage error) is a distortion of MAD (mean absolute error). It is a percentage value and therefore easier to understand than other statistics. The smaller the MAPE value, the higher the accuracy of the prediction model. In the three models, the MAPE value of the QPSO is the smallest, and its accuracy is the highest. Table 4 is the data comparison of the three models of tianfeng securities. From Table 4, we can see that the fitting effect of QABC and QPSO is good, and the data of QABC are better than QPSO. However, this does not mean that the prediction effect of QPSO is not good, which just means that the prediction effect of QPSO is more stable and more suitable for prediction, although the size of QPSO may have some influence on it, but the effect is far less than in the other two models.

# 4. CONCLUSION

By analyzing three models, QPSO is the best place to make predictions. The R2 values of CITIC Securities and tianfeng securities are all above 0.9, the fitting effect is good, and the values of MSE, RMSE, MAPE and MAD are all small and within a reasonable range. Although the QPSO is not the best in the data comparison of tianfeng securities, it is relatively stable, and the change of size has little effect on the QPSO, so it's the best of the three models for making predictions. The prediction effect of QABC in CITIC Securities is not very good, but the data of tianfeng securities is the best in the three models, the stability is not high, and the prediction effect of QFOA is similar to that of tianfeng securities. In conclusion, QPSO can predict the trend of stock better than the other two models.

# **REFERENCE:**

 Ge, Z.Y., & Chen, H.T.,(2016), Implementing Java in Genetic Programming Adaptive Modelling and Its Application in Stock Price Prediction, Computer Applications and Software, 33(3):121-125, 155.

- Ran, Y.F., & Jiang, H.X., (2017), Stock Prices Prediction Based on Back Propagation Neural Network and Support Vector Regression, Journal of Shanxi University(Nat.sci.ed.), 41(1):1-14.
- 3) Chen, Y.S., Tang, Z.J., Luo, Y., & Yang, J., (2018), Research on stock price prediction based on Xgboost algorithm with pearson optimization, Information Technology, 9:84-89.
- 4) Wang, Y.,& Guo, Y.K.,(2019), Application of Improved XGBoost Model in Stock Forecasting, Computer Engineering and Applications, 20:202-207.
- 5) Jin, J.H., Sun, J., Zhang, A.T., Zhang, B., (2020), Route Planning of Unmanned Craft Based on Quantum Particle Swarm Optimization, Ship Mechanics, 3: 352-361.
- 6) Shi, J.N., Zou, J.Z., Zhang, J., Wang, C.M., & Wei, Z.C., (2020), Research of stock price prediction based on DMD-LSTM model, Application Research of Computers, 3:662-666.
- 7) Ding, W.J., (2021), Comparison of ARIMA Model and LSTM Model Based on Stock Forecast, Industrial Control Computer, 34(7):109-116.
- 8) Zhang, R.M., & Zhang, H.M., (2021), Comparative Analysis of Stock Forecast Based on BP Neural Network and ARMA-GARCH Model, Journal of Science of Teachers' College and University, 41(5):14-20.
- 9) Hu, Y.W.,(2021), Stock Forecast Based on Optimized LSTM Model, Computer Science, 48(6A):151-157.
- Xu, Y.M., Wang, Z.H., & Wu, Z.X., (2021), Predicting Stock Trends with CNNBiLSTM Based Multi-Feature Integration Model, Data Analysis and Knowledge Discovery, 5(7): 126-137.
- 11) Liu,K.,He,J.H.,Huang,Y.,Liang,Y.,& Zhang,Y.,(2016),Quantum behaved particle swarm optimization algorithm for solving WTA problem with ordering mapping, Application Research of Computers,33(3):765-767.
- 12) Zhao, J.,& Cheng, C.,(2017),Improved QPSO algorithm based on search history, Computer Engineering and Applications, 53(9):41-46.
- 13) Zhou,D.,(2018),An Optimization Method of SVM Parameters Based on Improved QPSO Algorithm,Jisuanji Yu Xiandaihua,9:27-31.
- 14) Tang,R., Chen, Q.C.,& Lei, X.F.,(2019),GQPSO-WNN Short-Term Traffic Flow Forecasting Based on Phase Space Reconstruction, Computer Applications and Software,36(7):311-316.
- 15) Tan, Z.F., Tan, C.X., Pu, L., & Yang, J.C., (2020), Two-Layer Game Model of Virtual Power Plant Applying CIQPSO Algorithm, Electric Power Construction, 41(6):9-17.
- 16) Li, F., Wu, Z.H., Liu, K.R., & Ge,E.Q.,(2021), R2 Indicator and Objective Space Partition Based Many-Objecti ve Particle Swarm Optimizer, Control and Decision, 36(9): 2085-2094.
- 17) Zhang, Y., Zhou, W.J., Wang, X.X., & Han, M.S., (2021), Improved Particle Swarm Optimization Algorithm for Inversion of Evaporation Ducts, Electronics Optics & Control, 28(6):1-6.
- 18) Ma, S.Q., Tang, H., Li, Y., & Lei, Y.J.,(2021), A Traffic Scheduling Strategy Based on Particle Swarm Optimization in Data Center Network, Telecommunication Engineering, 61(7):865-871.
- 19) Zhang, Q.,(2021), Ship Network Security Prediction Model Based on Particle Swarm Optimization Neural Network, Ship Science and Technology, 43(7A):163-165.
- 20) Christian, H., Ian, F.,& Jarrad, W.,(2018), Corticospinal excitability during motor imagery is reduced in young adults with developmental coordination disorder, Research in Developmental Disabilities, 72: 214-224.