Stock Market Forecast Based on Wavelet Neural Network Optimized by Cuckoo Search

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Abstract—**As a typical nonlinear deterministic dynamical system, stock market can be predicted by Wavelet Neural Network. Since Cuckoo Search is a new heuristic bionic group intelligent optimization algorithm, it can be widely used in various optimization problems. In this paper, we use Cuckoo Search (CS) to optimize the initial parameters of wavelet neural network. Results of the experiment show that the optimized CS-WNN has higher prediction accuracy than the traditional WNN in stock market forecast.**

Keywords-Cuckoo Search; Wavelet Neural Network; Stock Market Forecast

I. INTRODUCTION

Stock market is popular due to its flexible investment and high rate of return, but because of the risks and opportunities coexisting in the stock market, bankrupts are everywhere. On account of particularity, non-linearity, high noise and sensitive factors of the stock market system, it is very difficult to forecast the stock market, but the enthusiasm for the securities market has been increasing since the birth of the stock market. Wavelet Neural Network has been developed in recent decades, combining the advantages of neural network and wavelet analysis, both nonlinear approximation of neural network, self-organizing learning, simple structure etc, and time-frequency localization properties of wavelet analysis and black box identification ability, so that it is more powerful to approach the stock price trend. Compared with the traditional forward-type network, WNN combines the advantages of nonlinear systems and artificial intelligence technology to avoid blindness of structural design and defects of easily falling into the local minimum, so it can grasp the high-frequency information more accurately, and has simple structure with less time required to run. However, the wavelet neural network has the shortcomings of the initial value. In view of this problem, this paper introduces the cuckoo search algorithm to optimize the initial parameters of WNN, and proposes a WNN forecast algorithm based on the cuckoo search algorithm.

II. WAVELET NEURAL NETWORK

Wavelet Neural Network (WNN) is a neural network based on BP neural network topology, and the difference between traditional BP neural network is the transfer function which is changed into wavelet basis function of the hidden layer node. The topological structure of WNN is shown in Fig1.

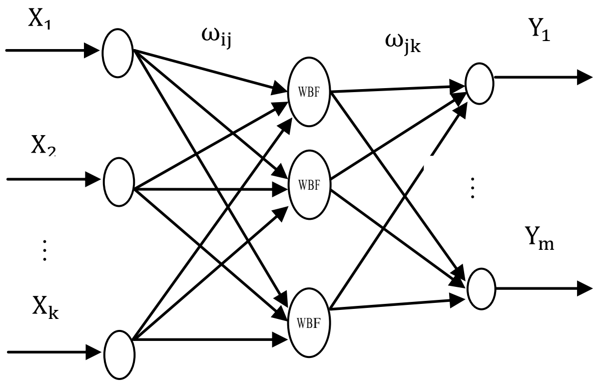

Figure 1. Topological structure of WNN

X_1, X_2, $\cdots$, X_k are input parameters of WNN, $Y_1, Y_2, \cdots, Y_m$ are predict outputs of WNN, ω_{ij} and ω_{jk} are weights of WNN.

When the sequence of input layer is x_i (i= 1, 2, • • •, k), calculation formula of the output in hidden layer is as below:

$$h(j) = h_j\left[\frac{\sum_{i=1}^{k}\omega_{ij}x_i - b_j}{a_j}\right] \quad j = 1,2,\cdots,l \tag{1}$$

h (j) refers to the output value of the node j, ω_{ij} is the connection weights for the input layer and hidden layer. b_j is translation factor of wavelet function, a_j is the expansion factor of the wavelet basis function, h_j is the wavelet basis function. In this experiment, the wavelet basis function is Morlet mother wavelet basis function, its formula is expressed as below:

$$y = \cos(1.75x)e^{-\frac{x^2}{2}} \tag{2}$$

Fig 1 Topological structure of wavelet neural network

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$$y(k) = \sum_{i=1}^{l}\omega_{ik}h(i) \quad k = 1,2,\cdots, m \tag{3}$$

ω_{ik} refers to the weight for hidden layer and output layer, h(i) is the output of the node i in hidden layer, l is the number of nodes in hidden layer, m is the number of nodes in output layer.

The weight correction algorithm of WNN is similar to BP neural network weight correction algorithm. The gradient correction method is used to modify the weight of the network and the wavelet basis function parameters, so that the WNN prediction output is approaching the expected output, and the WNN correction process is as follows :

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A. Calculate the errors of network prediction

$$e = \sum_{k=1}^{m} yn(k) - y(k) \quad (4)$$

$yn(k)$ refers to expected output, $y(k)$ is predict output of wavelet neural network.

B. Correct the weights of the WNN and the wavelet basis function coefficients according to the prediction error e

$$\omega_{n,k}^{(i+1)} = \omega_{n,k}^{i} + \Delta\omega_{n,k}^{(i+1)} \quad (5)$$

$$a_k^{(i+1)} = a_k^{i} + \Delta a_k^{(i+1)} \quad (6)$$

$$b_k^{(i+1)} = b_k^{i} + \Delta b_k^{(i+1)} \quad (7)$$

Here, $\Delta\omega_{n,k}^{(i+1)}$, $\Delta a_k^{(i+1)}$, $\Delta b_k^{(i+1)}$ are calculated from the network prediction error.

$$\Delta\omega_{n,k}^{(i+1)} = -\eta \frac{\partial e}{\partial \omega_{n,k}^{(i)}} \quad (8)$$

$$\Delta a_k^{(i+1)} = -\eta \frac{\partial e}{\partial a_k^{(i)}} \quad (9)$$

$$\Delta b_k^{(i+1)} = -\eta \frac{\partial e}{\partial b_k^{(i)}} \quad (10)$$

Here η means learning rate.

III. CUCKOO SEARCH

The cuckoo search algorithm is a new meta-heuristic algorithm proposed by two famous scholars of Cambridge University in the UK named Yang and Deb, based on the breed characteristics and flight of cuckoo. Scholars used many functions testing, and the results showed that CS was better than PSO and GA in some respects. It has many advantages, such as strong capability of global searching, quick convergence, less parameters, good universality and robustness.

Studies find that cuckoos lay eggs in other bird's nest, called host nest. Once host birds find the truth on the spot, there will be a sharp conflict. If host birds find the egg is not theirs, they will give up the egg or nest. As a result, cuckoos usually choose nests which host birds has laid eggs just now, thus once cuckoo's eggs are kept, they will be hatched quicker than other eggs. And cuckoo larvae will naturally push other eggs out, therefore, host birds will raise the cuckoo. Besides, plenty of scholars find that many animals and insects have the characteristics of Lévy flight [1-4]. Yang has assuming the cuckoo search algorithm into three ideal conditions [5]:

- Each cuckoo produces only one egg at a time, and randomly chooses a nest to store
- In the process of finding nest, the best bird nest will be retained to the next generation;
- The number of available bird nests is fixed, and the probability that the foreign eggs are found in the bird's nest is p, $p \in [0,1]$.When host bird find cuckoo's egg，it will establish a new nest.

Through the assumption of the above three ideal states, the update formula of the location and path of the cuckoo search is as follows.

$$X_i^{t+1} = X_i^t + \alpha \oplus \text{Lévy}(\lambda) \quad (11)$$

X_i^t refers to the location of ith nest when it changes to the tth generation, $\oplus$ refers to point-to-point multiplication. ,α is the step control value aimed at controlling search range, indicates cuckoo's random search path, whose direction and length are uncertain. In order to make it better applied to CS algorithm, a value named α is defined in paper[6] to adjust the path length, α is a constant which is greater than zero, in this paper we choose α as 0.01

In the 1930s, the French mathematician Laiwu proposed the Lévy (λ) distribution. Since then Yang and others had further studied this formula, they made Lévy(λ) distribution simpler and use Fourier transform to get probability density function in the exponential form.

$$\text{Levy}(\lambda) \sim \mu = t^{-\lambda},\ 1 < \lambda \leq 3 \quad (12)$$

Here λ is an exponent, which is a probability density function with a heavy tail. Although this function can describe the random process of the cuckoo algorithm in essence, it is extremely difficult to achieve in programming. Therefore, Yang and his mates use a formula(13), which was proposed in 1992 by Mantegna, aiming at simulating the path of Lévy flight and jump path.

$$s = \frac{\mu}{|v|^{1/\beta}} \quad (13)$$

Here s means the path of Lévy flight and jump Lévy(λ).$\beta=\lambda-1$，$0<\beta<2$，in this paper, $\beta=1.5$[7]

μ and v are normal distribution random number, which are shown as below, obeying normal distribution.

$$\begin{cases} u \sim N(0,\ \sigma_u^2) \\ v \sim N(0,\ \sigma_v^2) \end{cases} \quad (14)$$

$$\begin{cases} \sigma_u = \left\langle \dfrac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma\left(\frac{1+\beta}{2}\right)2^{(\beta-1)/2}\beta} \right\rangle \\ \sigma_v = 1 \end{cases} \quad (15)$$

We can see Lévy flight depends on parameters μ and v, which are random number. Therefore, high randomness in the process of searching and strong ability of global optimization will be reached. Here Pa=0.25, which refers to the probability of the host bird abandoning the eggs

IV. STOCK MARKET FORECAST BASED ON WAVELET NEURAL NETWORK OPTIMIZED BY CUCKOO SEARCH

Closing price of the stock market is chosen as sample indicator. In the experience, 5 trading days are chosen to be the input value of the network, the 6th day is chosen to be the output value, that is there is 1 node in the output layer, 4 nodes are chosen in the hidden layer.

Step1. Import the data and normalize the data according to the formula(16), and split the 340 data into the training data set (the first 311) and the forecast data set (the last 29).

$$X = \frac{X' - X_{min}}{X_{max} - X_{min}} \quad (16)$$

Step2. Initialize the wavelet neural network, 5 nodes are in the input layer, 4 nodes are in the only hidden layer, 1node is in the output layer. Weights, the translation factors and scalability factors are randomly generated. Learning rate and number of iterations are also determined. Here in this experience learning rate is 0.01, number of iterations is 100, prediction accuracy is 0.99.

Step3. We assume that the number of the nests, denotes as N_{nest}, is set as 25, the probability of the host bird abandoning the eggs is 0.25. The number of iterations is 200, The random location of N_{nest} nest is $W = (W_1, W_2, \cdots, W_{nest})^T$, each nest W_i contains s papameters.($s = 5 \times 4 + 4 + 4 + 4 \times 1 = 32$). Wavelet

Neural Network randomly obtained a set of data, then begin training according to the original parameters of each nest, and calculate predicted value of the nests, at last find out the nest whose predicted error is smallest among all these nests, denoted as W_{best}, and keep it to the next generation.

Step4. According to the location and path updating formula (11), every nest except for W_{best} should be updated. Then we calculate the error through WNN, and compare with other nests' predicted error besides W_{best}, then replace the nest with large error by ones with less error, in order to achieve the better location of current generation. New locations are denoted as W_{new}, $W_{new} = (W_{new1}, W_{new2}, \cdots, W_{newnest})^T$

Step5. A random number r is generated, once r is larger than Pa, a new set of nests' location will randomly be generated. We calculate the new nests' error through WNN, and compare with predicted error of the sequence of nests in W_{new}.Then we replace the nests with large error by nests with small error, and we get a new generation of best locations. $W'_{new} = (W'_{new1}, W'_{new2}, \cdots W'_{newnest})^T$

Step6. We find out the nest with best location in W'_{new}, and denote it as W_{best}, if the number of iterations or prediction accuracy is not achieved, we return to step 4 and continue searching, otherwise output the current W_{best}.And it is assigned to WNN as weights, translation factors and expansion factors.

Step7. We input the training data to WNN to train, When number of iterations or prediction accuracy is achieved, WNN stops studying, and save all current parameters.

Step8. We input test data, and do actual forecast. Then we compare the forecast result of CS-WNN with traditional WNN in stock market.

V. EXPERIMENT RESULT

A. Prediction Result

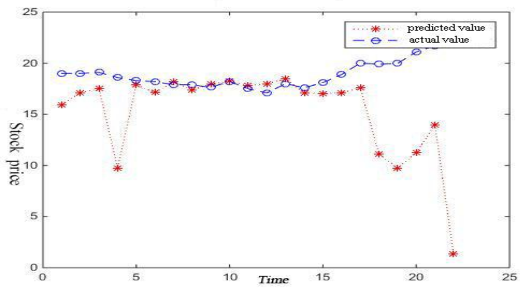

Figure 2. Prediction Result of CS-WNN

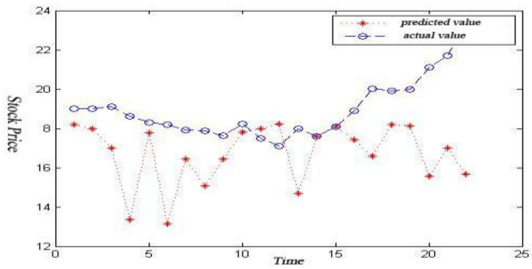

Figure 3. Prediction Result of WNN

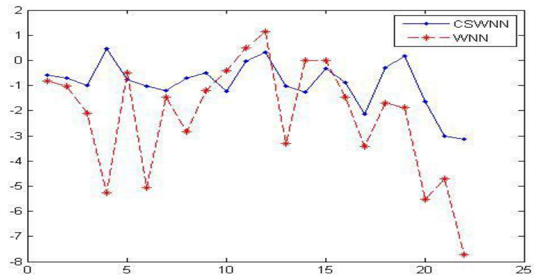

Figure 4. Error of Actual Output and Desired Output of CS-WNN and WNN

We do 50 experiences, and the relatively superior result is shown in Fig 2, Fig 3 is the prediction result of WNN. Average error of CS-WNN and WNN is compared in Fig 4.

B. Performance Comparison

In order to have a straight comparison of CS-WNN and WNN in stock market forecast, we give Mean Absolute Error (MAE) and Mean Squared Error (MSE) in TABLE I.

TABLE I. INDEX SOFTWARE SYSTEM

	MAE	MSE
CS-WNN	0.9742	1.1568
WNN	2.3643	3.1354

VI. CONCLUSION

In this paper, we use Cuckoo Search (CS) to optimize the initial parameters of wavelet neural network. The result of experiments shows that CS-WNN is better than WNN in degree of fitting and forecast accuracy. But in consideration of influences from policies and social events, we should think more carefully about stock market forecast with multiple input parameters.

[1] Brown C, Liebovitch L S, Glendon R. L'evy flights in Dobe Ju [C] / /hoansi foraging patterns, Human Ecol, 2007, 35: 129-138

[2] Pavlyukevich I. L'evy flights, non-local search and simulated annealing [J] . J. Computational Physics, 2007, 226(2) : 1830- 1844.

[3] Pavlyukevich I. Cooling down Lévy flights [J] . Journal of Physics A Mathematical and Theoretical, 2007, 40(41) : 12299-12313.

[4] Reynolds A M, Frye M A. Free-flight odor tracking in Drosophila is consistent with an optimal intermittent scale-free search [C] / /PLoSOne, 2007, 2: e354.

[5] Yang X S, Deb S. Engineering optimization by cuckoo search [J] . International Journal of Mathematical Modeling and Numerical Optimization, 2010, 11(4) : 330 343.

[6] Yang X S, Deb S. Cuckoo search via Lévy flights [C] / /Proceedings of World Congress on Nature & Biologically Inspired Computing. Piscataway: IEEE, 2009: 210- 214.

[7] Yang X S, Deb S. Engineering optimization by cuckoo search [J] . International Journal of Mathematical Modeling and Numerical, 2010, 1(4) : 330- 343.