Feedback function optimization of financial market forecast hopfield algorithm

Meiyan Lin

School of Science, Dalian Jiaotong University,
Dalian 116028, Liaoning, China

Abstract
For standard Hopfield network algorithm in the financial market practical forecast still exists problems of low efficiency, low accuracy and so on. This paper puts forward a financial markets prediction model based on improved simulated annealing algorithm optimization Hopfield algorithm. Before using the simulated annealing algorithm to optimize the feedback function of Hopfield algorithm, we should improve the operation efficiency of the algorithm and reduce the computation burden of fusion algorithm, first of all, we use Cauchy distribution as a disturbance distance, and adopt the variable metric method which is decided by the random number and the current optimal solution to improve the solving way of annealing algorithm, and then modify the annealing progress, and keep proper control of cooling process, finally, fuse the improved simulated annealing algorithm and Hopfield algorithm, construct financial market forecast model. Through the simulation experiments show that the proposed improved simulated annealing algorithm greatly reduces the standard algorithm computational complexity, after it is fused with DHNN algorithm, and it did not reduce the operational efficiency of the original algorithm, and the proposed SA - DHNN algorithm improves the prediction accuracy of the original algorithm greatly in the application of financial market forecast.
Key words: FCM ALGORITHM, NUCLEAR FUZZY, CLUSTERING ALGORITHM, SEARCH OPTIMIZATION

Introduction

Under the traditional framework of efficient market theory, financial market analysis has been dominated by linear model. Based on the fractal market theory, use the nonlinear method which is closer to the market to research the market, it can reveal the local and global characteristics of financial markets better and improve the ability of forecasting, decision-making and risk control [1]. Research of the chaos trade model theory can outreach the technology analysis extension, tamp the theoretical basis of technology analysis, and promote the innovation and development of the financial market technical analysis method [2]. Because China's financial market has just started, the data characteristics is different from the traditional western financial markets, and carrying on the empirical research of the model can effectively avoid the so-called "data into bias", that is the optimal model which is got by the historical data analysis for many times, it may be a kind of "Over-fitting", in the it does not have ability to predict future [3].In this way to provides a new empirical content to the economic chaos theory, thus to promote the development of financial theory.

First of all, in the bank or bankruptcy prediction, decision-making of buy and sell stocks and credit card applications these three fields, the classification of the financial data is the problem demanding prompt solution. Shinong wu et al., in order to solve the problem of enterprise financial early warning, three kinds of prediction model is set up by the traditional analysis method, the experimental results show that judgment accuracy of 4 years before the financial early warning can be higher than 72% in [4].The artificial intelligence method also has wide applications in the field. Amir F.A tiya established a neural network model, the data sample is divided into two parts for training and prediction, the final prediction accuracy reached 85.5% [5].Lu Xiu ze builds a dual neural network in the study, through the prediction of stock market inflection point, thus to make decisions of stock’s "buy" or "sell" [6].Liu Jihai et al., establish a support vector machine (SVM) model to solve the problem of credit card management score, experiments show that the model has good performance, from the comparative experiments can also be learned that the classification accuracy of the classification model is higher than Logistic regression algorithm [7].Mukherjee uses supporting vector regression machine to predict chaotic time series, and the predicted results are compared with the result of many kinds of prediction model, the experimental results show that the performance of supporting vector machine is good[8].Tao Zhang et al., establish a hybrid support vector machine (SVM) model, forecast the future performance of the stock market, and have achieved good results [9].Cai and others use principal component analysis method to extract the characteristics of two classes of stocks respectively, and support vector machine (SVM) is carried out on the two kinds of stock classification, the experimental results is superior to the traditional classification method[10].Wu and others combine the independent principal component analysis method with support vector machine (SVM), a financial time prediction model is constructed. The compared experimental results show that independent component analysis method is superior to other methods of feature extraction [11]. Abolhassani uses particle swarm optimization algorithm to choose input variables, in a large number of input variables, extract the characteristics which have important information in the input variables, and then support vector machine (SVM) regression model is established, the experiment proves that the support vector machine (SVM) regression model based on particle swarm is superior to pure traditional support vector machine (SVM) model [12].

For the defects of Hopfield algorithm in the financial markets, this paper proposes a financial markets prediction model based on improved simulated annealing algorithm optimal Hopfield algorithm, and the experimental simulation is done according to the actual data, the validity of the model is verified.

Hopfield algorithm defect analysis

Discrete Hopfield Neural Networks (DHNN) is a kind of single layer, input and output for binary feedback network, it is mainly used for associative memory. There are one or more minimum points or balance points of network energy function. When the network's initial position is determined, the network status according to their working rules to the direction of energy decreasing, finally close to or reach the balance point. This balance is known as the attractor. If trying to design the pattern of the memory required by network into a balance point of certain network state, when network starts from an initial state which is closer to the memory pattern, status updates by Hopfield operation rules, the network is stable at the minimum point of energy function, namely it is the state corresponding with the memory model. This completes the associative memory process of the part information or distortion information to all or complete information.

DHNN network computation formula is as follows:

$$U_i(t+1)=\sum_{j=1}^{n} w_{ij}x_j(t)-\theta_j \tag{1}$$

$$x_i(t+1)=\text{sgn}[u_i(t+1)] \tag{2}$$

Among them, $x=[x_1,x_2,...,x_n]^T$ is the state vector of the network, its component is the output of n nerve cell, only take 1 or – 1. $\theta=[\theta_1,\theta_2,...,\theta_n]^T$ is the threshold vector of the network. $w=[w_{ij}]_{n\times n}$ is the connection weight matrix of the network, The element w_{ij} represents the connection power of the j th neuron to the i th neuron, it is symmetric matrix, $w_{ij}=w_{ji}$. If $w_{ij}=0$, then the network is not feedback; Otherwise, it is feedback.

In the equation, $\text{sgn}(x)$ is symbolic function

$$\text{sgn}(x)=\begin{cases}1, x\geq 0\\ 0, x<0\end{cases} \tag{3}$$

The connection power of the Hopfield net is designed, the main idea of the design method is to make the memory pattern corresponding to the minimum value of network energy function.

If there are m nD memory patterns, we need to design right of network connection w_{ij} and threshold value θ, make the m patterns be the m minimums of network energy function. The commonly used design method is " Method of cross product". Set:

$$U_k = [U_1^K, U_2^K, ..., U_n^K], k = 1, 2, ..., m \quad (4)$$

$$U_i^K \in \{0,1\} \quad (5)$$

Among them, m is pattern category number, n is the dimensions of each kind of model. U_k is the vector expression of patter k.

The $m(m \le n)$ memory mode vectors of network memory should be pairwise orthogonal, it satisfies the equation below:

$$U_i' U_j = \begin{cases} 0, j \ne i \\ n, j = i \end{cases} \quad (6)$$

Threshold of each neuron $\theta_i = 0$, connection weight matrix of network is calculated by the type below:

$$W = \sum_{k=1}^{m} U_k U_k' \quad (7)$$

Then all the vector U_k are stable point in $1 \le k \le m$.

Usually, the activation function of Hopfield neural network uses sigmoid function. Sigmoid function is a monotone increasing differentiable function, due to its monotonicity, its inverse function is only one. The output of each neuron can be shown by the monotone increasing differentiable functions, and the input not only has relationship with input neurons, it is also associated with connection weights, general

$$v_i = f(U_i) = \tanh(\alpha U_i) \quad (8)$$

Among them α is steepness coefficient, It mainly controls the gradient of the activation function, when $\alpha \to \pm\infty$, activation function $f(\cdot)$ can be seen as symbolic function, when $\alpha \to 0$, activation function $f(\cdot)$ can be regarded as a limiting function. when $U_i \to \pm\infty$, $v_i \to \pm 1$, it limits the scope of the output of the network. When $\alpha = 5$, activation function $f(\cdot)$ and its inverse function $f^{-1}(\cdot)$ is shown in figure 1.

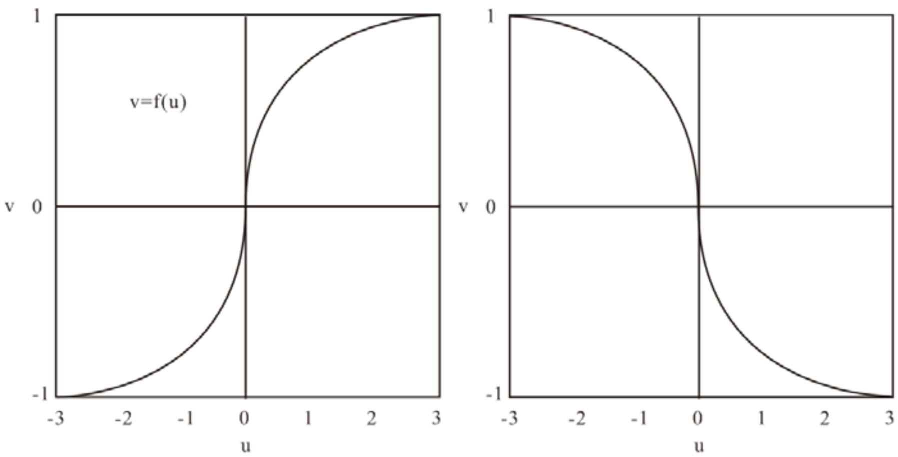

Figure 1. Activation function and its inverse function Legend

However, in view of the algorithm complexity explosion problem of the neural network model, although it uses the massively parallel processing way, but sometimes the computing complexity of the neural network model has little relationship with the number of neurons, and it has much relationship with the calculated sample of problem. So in the paper, the improved simulated annealing algorithm is adopted to the feedback function optimization.

Feedback function optimization based on simulated annealing

The computational efficiency optimization of simulated annealing algorithm

Before using the simulated annealing algorithm to optimize the feedback function of the Hopfield algorithm, first of all, this paper optimize the operation efficiency of the algorithm, reduce the computational complexity of fusion algorithm.

(1) Optimize the disturbance model

Disturbance model of the simulated annealing have important effects on the algorithm convergence speed, but most of algorithm just randomly select a node to disturb, fixed disturbance model is a common function, it is not varies with temperature, so it can lead the algorithm to slow convergence speed. So this paper uses a new disturbance model, the new perturbation model uses Cauchy distribution as a theory of the perturbation distance, the distribution can be expressed as:

$$p(\Delta x) = \frac{1}{\pi}\frac{T}{T^2 + (\Delta x)^2} \quad (9)$$

It can be deduced

$$\Delta x = T\tan(\pi \cdot z) \quad (10)$$

Among them z is random number, data range is $[0, 0.5]$. In task graph, Δx is the change number of the node which moves from the current partition to new partition, namely it is the distance between current partition and new partition. Because the total number of nodes and the annealing temperature value have the numerical and scope differences, therefore, so Δx needs to be normalized processing. But $\Delta x \in [0, N]$, then the inner loop cap of computing complexity of the algorithm is $o(K \cdot N)$, among them N is the number of jobs, K is the annealing number of each temperature, and it is constant number, Obviously the computational complexity of the inner loop is only related to N, when the number of tasks N is relatively large, the algorithm inner loop computation time will increase greatly.

Set the outer cooling times of random perturbation model simulated annealing algorithm as M, then the using computational complexity of the perturbation model algorithm is $o(M \cdot K \cdot N)$. So in extreme cases, the computing time of improved perturbation model algorithm is longer than random disturbance model, so in this paper, we do the processing to Δx, in order to reduce the computational complexity of the inner loop , make Δx change with T at the same time, the improved method is as follows:

$$\Delta x = \varepsilon \Delta x \quad (11)$$

Among them, ε is a smaller number. So the computational complexity of inner circulation after improvement is $o(K)$, computational complexity is reduced greatly, meanwhile the processed Δx is still the function of T, it has larger disturbance distances at high temperature, it is able to search in a larger scope, it only searches in the current classification at low temperature, it can accelerate the convergence speed.

(2) Optimize the solution way

In the way of solution, this paper combined with the variable metric method, puts forward the concept of effective offset. Effective offset refers to the offset when the current solution is accepted. If the last offset is not effective offsets, solution generating function is improved as follows:

$$Y_i^k = X_i^k + Z_i^k \quad (12)$$

$$Z_i^k = \frac{W_i T_i (b_i - a_i)/10}{\sqrt{\sum_{j=1}^{n} W_j^2}}\left|\frac{1}{|U_i|^m} - 1\right|, i = 1, 2, ... \quad (13)$$

In the equation, X is iterative initial solution, Z is iterative offset, Y is iteration data processing, U 、 W is $[-1,1]$ uniformly distributed random quantity, i is the weight vector, a_i and b_i are the lower limit and upper limit of i th weight of vector, $m \geq 1$ is a constant, $m = 3$.

If last offset is effective offset, the implementation of variable metric method: if penalty function value of the accepted current solution is reduce, the offset mark for success; Otherwise the offset mark for failure. In this paper, the generating function of the deviation of the next iteration is as follows:

$$Z_i^k = \begin{cases} 2.3Z_i^k, Z_i^k \leq 1.0e10 \\ -Z_i^k / 1.7, Z_i^k \geq 1.0e-8 \end{cases} \quad (14)$$

Equation (12), (13), (14) can improve the calculation efficiency and reliability of the simulated annealing algorithm, on the one hand it keeps low speed under the proper temperature, on the other hand, it makes the created random vector to keep a certain degree of distribution.

In order to improve the effect of chemotaxis search near the minimum, variable metric method decided by the random number and the current optimal solution are used, this paper puts forward a new search interval calculation method:

$$b_i' = \begin{cases} l_i + (b_i - a_i)/n_i, b_i' \leq b_i \\ b_i \qquad\qquad\qquad , b_i' > b_i \end{cases} \quad (15)$$

$$a_i' = \begin{cases} l_i + (b_i - a_i)/n_i, a_i' \geq b_i \\ a_i \qquad\qquad\qquad , a_i' < b_i \end{cases} \quad (16)$$

Among them, l_i is the component of the current optimal solution; n_i is the pseudo random number of 1 to 20, it is used to shorten the search range, improve the search efficiency. In local fine search phase, shrink the adaptive factor according to certain proportion at the same time of cooling down

(3) Optimize annealing speed

Annealing process is also the important parameter to control the algorithm convergence speed, it can be seen from the pseudo code of simulated annealing algorithm, the temperature is one of the two conditions of control algorithm is terminated, and the temperature is controlled by annealing process, the annealing schedule speed directly affect the rate of the algorithm convergence. Rapid annealing method is as follows:

$$T_k = \frac{T}{k} \tag{17}$$

And annealing schedule is:

$$T_k = (\alpha)^k T \tag{18}$$

T is the initial temperature, k is the k th temperature declining process, α is cooling factor, α 's value is between 0.92~0.99,it is usual 0.96, T_k is the exponential function of k, but $\alpha \to 1$ make the speed is slow. But annealing schedule function is inverse function, decline speed is faster than the standard simulated annealing algorithm annealing schedule, so the annealing progress can speed up the end of algorithm, but it can reduce the number of outer loop algorithm, the search scope of the algorithm does not cover enough solution space, it may be over when algorithms do not find the approximate global optimal solution, so in this paper, the annealing schedule is modified, the cooling process is appropriately controlled, through making k multiply by a weight $A(A<1)$ to slow cooling rate, So that you can fully iterative algorithm, the improved annealing schedule is as follows:

$$T_k = \frac{T}{A \cdot K} \tag{19}$$

Improved annealing process can overcome the defect that annealing too fast lead to the cover solution space is not enough, the algorithm has been the end under the condition that it does not get the approximate optimal solution, at the same time speed slightly faster than the speed of the standard simulated annealing algorithm, so that you can fully iterative algorithm and get the approximate optimal solution.

Feedback function optimization

DHNN has the characteristics of parallel processing, so its convergence speed is fast. In this chapter, DHNN combined with simulated annealing algorithm (SA) thought well overcomes the defect of local optimal solution. The SA in the solution space by updating the current optimal value, finally find the global optimal solution, making the SA - DHNN algorithm a rapid, global intelligent optimization algorithm.

SA - DHNN computational steps can be summarized as the following five steps:

(1) The initialization parameter

Initial temperature T, should be enough big, stable speed v, the number of neurons N, the number of iterations L, the initial value of neurons V_0, the algorithm of iterative starting point.

(2) Gradually increases with the number of iterations of T, v to rate N decreases.

(3) We iterate the input and output of the neural network, when j increased from 1 to αL, where $\alpha = 1/I$ .With the convergence of energy function to produce αL frequency data processing, namely every after αL DHNN iteration, will produce a set of data processing, making the network transition to the new state, to prevent fall into local extremum.

(4) Set the current optimal solution for V, $C(V)$ as the evaluation function. On the basis of the data V processing new V', calculate $\Delta t = C(V') - C(V)$, if $\Delta t < 0$, then accept the new V' for the current solution, or otherwise probability $\exp(\Delta t / T)$ accept V' for the current solution.

(5) Determine whether it meets the termination conditions, if it meets the termination conditions, the current output solution as the optimal solution, or return to step (2). Termination conditions usually set a number of consecutive data processing, which are not acceptable.

Algorithm performance simulation

In order to verify the performance of the improved algorithm proposed in this paper, processing simulation experiments on it. First of all, simulate the operation speed performance of simulated annealing algorithm and the improved simulated annealing algorithm proposed in this paper simulation, the results shown in figure below.

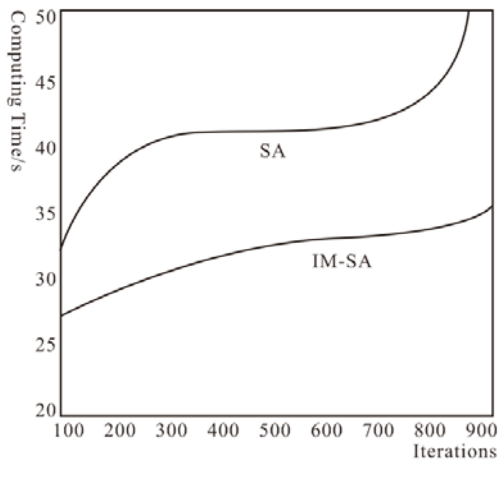

Figure 2. Simulation results of operation speed

Then, simulate the operation speed performance of proposed SA - DHNN algorithm and standard DHNN algorithm, the results shown in figure below.

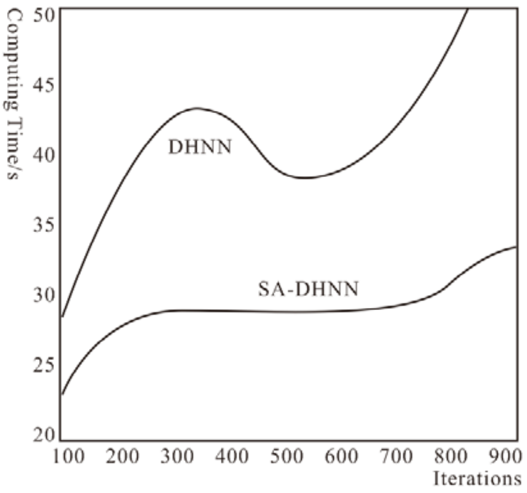

Figure 3. Simulation results of operation speed

Finally, according to a certain part of the financial market data to forecast the simulation of SA - DHNN algorithm proposed in this paper, and compared with traditional DHNN algorithm, the result is shown in the following figure.

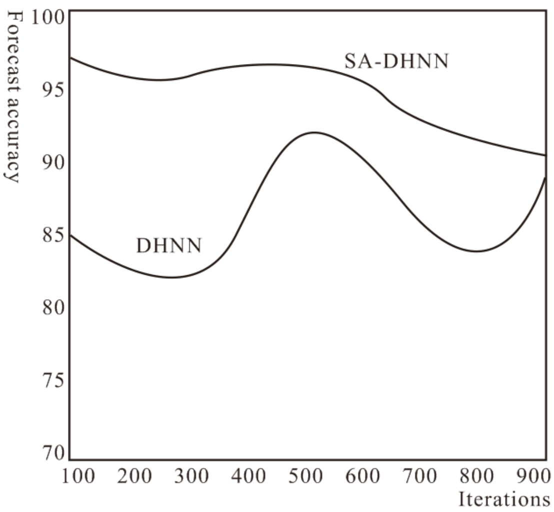

Figure 4. Financial market forecasting accuracy of the comparison results

From the above results we can see that the improved simulated annealing algorithm put forward in this paper greatly reduces the standard algorithm computational complexity, and combines it with the DHNN after fusion algorithm will not reduce the operational efficiency of the original algorithm. And the proposed SA - DHNN algorithm greatly improve the prediction accuracy of the original algorithm in the application of financial market forecast.

Conclusion

The financial system is an open complex system, there are intricate relations between each economic variable. Modern financial theory constituted with time value of money, asset pricing and risk management, and other three elements, the core problem is how to manage the inter-temporal optimal allocation of resources in uncertain environment. In view the importance of the stock returns and volatility sequences in the function of the portfolio and risk aversion, scientifically predicting the volatility of financial markets characteristics, grasping the law of volatility in financial markets and its structure to circumvent the prevention and management of financial risk monitoring is of great significance. Based on the defects of Hopfield algorithm in the financial markets, this paper proposes a prediction model of financial markets a optimization based on improved simulated annealing algorithm optimized Hopfield. The experimental simulation results show that the proposed improved simulated annealing algorithm greatly reduces the standard algorithm computational complexity, and combines it with the DHNN after fusion algorithm will not reduce the operational efficiency of the original algorithm. And the proposed SA - DHNN algorithm greatly improve the prediction accuracy of the original algorithm in the application of financial market forecast.

References

1. Rongxi Zhou (2014) An Optimization Model of Static Term Structure of Interest Rates Based on the Combinatorial Forecast Method. *Operations Research and Management Science*, 23(6), p.p.205-212.
2. Defang He (2014) Research on Prediction Market Based on Rules of Quasi-Financial-Future Exchange:Taking the NSFC Application as an Example. *Journal of The China Society for Scientific and Technical Information*,33(9), p.p.900-909.
3. Haofeng Lin (2014) China's financial conditions index and real estate development investment growth forecasts. *Commercial Age*, no.34, p.p.71-73.
4. Yang Gao (2014) International Carbon Finance Market Price Prediction Based on EMD-PSO-SVM Error Correction Model.China Polulation. *Resources and Environment*, 24(6), p.p.163-170.
5. Liping Liu (2014) The Comparative Analysis of Multidimensional Financial High Frequency Covariance Matrix’s Prediction Model. *Mathematics in Practice and Theory*, no.12, p.p.203-214.

6. Yanqiong Liu (2014) The financial cash flow statement and forecast. *Statistics and decision*,no.19, p.p.42-45.
7. Xiangfei Li (2014) Extraction and Forecasting of Financial Returns Based on Hybrid Method of EMD and STSA. *Systems Engineering*, 32(2), p.p.138-144.
8. Hongben Luo (2014) An Intelligent Hybrid Prediction for Financial Time Series Based on the Grey-ARIMA.*The Theory and Practice of Finance and Economics*,35(2), p.p.27-34.
9. Feng Liang (2014) Research on the Grey Forecast Model GM (1,1) of Loans of Financial Institutions. *On Economic Problems*, no.1, p.p.58-61.
10. Hairong Bian (2013) Study on Financial Crisis Prediction Model with Web Financial Information for Listed Companies.*Computer Science*, 40(11), p.p.295-298.
11. Guoxiang Xu (2013) Construction and Predictive Ability Research on China's Financial Conditions Index. *Statistical Research*, 30(8), p.p.17-24.
12. Lifang Liao (2013) Based on MODWT in application of predict financial data. *Computer Engineering and Design*, no.4, p.p.1346-1350.