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Study on Stock Trading Decision based on Particle Swarm Optimization Cyclic Radial Basis

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Abstract: The existing mature stock market data is analyzed based on the regularity and predictability of stocks. Firstly, a support vector machine is used with an appropriate kernel function to classify stocks that exhibit similar regularity. Secondly, an adaptive particle swarm algorithm is employed, which incorporates the speed change of extreme position. This algorithm utilizes the number of iterations of the radial basis network as the search position and the prediction accuracy of the training set as the adaptation function. The aim is to establish a multi-stock trading strategy for buying, selling, and holding. The classified stock data from the support vector machine is then selected, and the training set and testing set are defined. The simulation results demonstrate an average prediction accuracy of over 92% for the stocks, with a return ratio of 11.45%. This strategy enables stock traders to achieve high yield and high returns.

Keywords: Support vector machines; Adaptive particle swarm optimization; Stock decision model; Cyclic radial basis network

I. INTRODUCTION

With the rapid development of computer intelligence technology, the cross-fertilization of the fields of financial computational mathematics and artificial intelligence has been widely studied [1]. Quantitative trading, as a trading method that combines computer application technology with financial markets [2], gives trading strategies for buying, selling, and holding multiple stocks by analyzing existing mature stock market data to achieve high gains and returns for stock traders.

In traditional stock trading research, including multiple regression methods, time series models, BPNN and decision tree algorithms [3-8], good practical application results have been achieved. However, with the development of big data and artificial intelligence computing technology, the ability of data mining as well as knowledge discovery has been dramatically improved. In particular, the emergence of machine learning algorithms has led to further improvements in AI trading technology [9].

For parameter optimization problems, evolutionary algorithms have been widely used by scholars, such as ant colony algorithm, genetic algorithm, particle swarm algorithm and artificial fish swarm algorithm, etc. However, evolutionary search requires a complete search space, such as particle swarm mimicking the process of birds foraging for food within the woods, and ant colony mimicking the process of ants' path on the ground. Genetic algorithms refer to the mechanism of chromosome crossover mutation in human genetics and encode parameters as chromosomes for evolution. Ren Jun [10] constructed GSVM-L and ELSTM-L investment models and back tested and analyzed 133 constituent stocks in CSI 300 index, and achieved high investment returns and strong risk resistance; Fang Xuejun [11] gave a new multi-criteria Vague set stock decision-making method based on Rough approximation; with the development of big data and artificial intelligence computing technology, people's needs for data mining and knowledge discovery have also increased dramatically, especially in the decision-making computational speed needs to be further accelerated, so there is an urgent need for a faster, simpler and more accurate decision-making model.

In this paper, based on the regularity and predictability of the stocks in the above study, C-support vector machine is used to classify and predict different stocks, and based on the Adaptive particle swarm optimization (APSO) recurrent radial basis function (RRBF) to establish multiple stocks purchase and sell and hold trading strategies, and the model is validated through experiments. RRBF) to establish a trading strategy of buying, selling and holding multiple stocks, and the model is validated through experiments.

II. BASIC THEORY

2.1 C-Support Vector Machines

Support vector machine is a strong mapping classification algorithm that can quickly identify data features. The core of the support vector machine is the need to set the appropriate kernel function, has completed the mapping of different feature spaces. And Sig kernel function can activate the data sequence well and reduce the computation in the space of limited analysis.

$$\kappa(x_i, x_j) = \tanh(\beta x_i^T x_j + \theta); \beta > 0, \theta < 0 \tag{1}$$

Generally training sets mapped to higher dimensional spaces cannot be classified rigidly, and need to be softened for the model, which in combination with the support vector machine dyadic problem yields

$$\kappa(x_i, x_j) = \tanh(\beta x_i^T x_j + \theta); \beta > 0, \theta < 0 \tag{2}$$

Define the decision function of the support vector machine as

$$g(x) = \sum_{i=1}^{l} y_i \alpha_i^* \tanh(\beta \alpha^T{}_i x + \theta) + y_i - \sum_{i=1}^{l} y_i \alpha_i^* \tanh(\beta \alpha_i^T \alpha_j + \theta) \tag{3}$$

A classification function of $g(x) > 0$ would be in the first category and $g(x) < 0$ would be in the second category. The limitation of the support vector machine is that only two stock clusters can be classified at a time, but the number of stock classes will not be too many, and the number of classifications will basically not increase the computational effort of the model.

2.2 Adaptive particle swarm optimization

The variable in the support vector machine is first used as the particle number in the target search space

$$X_j = (x_j^1, x_j^2, \cdots, x_j^n), j = 1, 2, \cdots, m \tag{4}$$

The velocity of the particle is

$$V_j = (v_j^1, v_j^2, \cdots, v_j^n), j = 1, 2, \cdots, m \tag{5}$$

The updating equations for velocity and position are [11-14]

$$V_j^{k+1} = \omega V_j^k + c_1 r_1 (P_j - X_j^k) + c_2 r_2 (P_g - X_j^k) \tag{6}$$

$$X_j^{k+1} = X_j^k + V_j^{k+1} \tag{7}$$

The parameter in (6) is the learning factor which $c_1 = c_2 = k$, and V is particle velocity.

When the individual pole is reached, it then changes its moving speedto

$$V_j^{k+1} = \frac{1}{2}\left|X_j^m - X_j^1\right| + c(P_g - X_j^k), j = 1, 2, \cdots, m \tag{8}$$

When $P_j^n > P_j^m$ occurs at other positions, the individual's better position is shifted to X_j^n. At the same time, the node particle searches on both sides with a speed of $V_j^{k+1} = \omega V_j^k$ until the search stops when there is no better position in the global space.

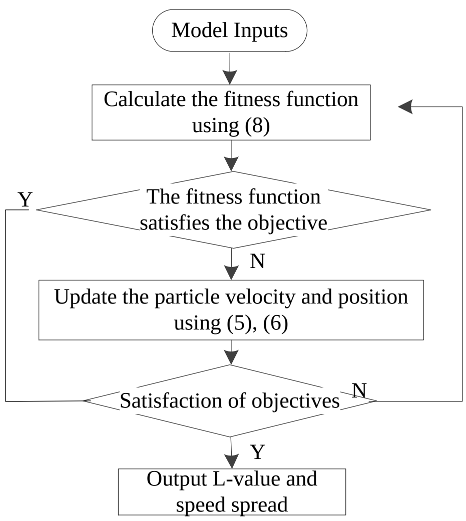

Fig.1. Adaptive Particle Swarm Optimization Steps

2.3 Circular Radial Basis Networks

Radial basis function (RBF) network has simple network nodes compared to BP network and can predict accurately when the sample size is small.RBF network contains input, output and hidden layers.In this paper, we add cyclic factors to the network structure and use particle swarm to change the number of nodes in the middle layer.

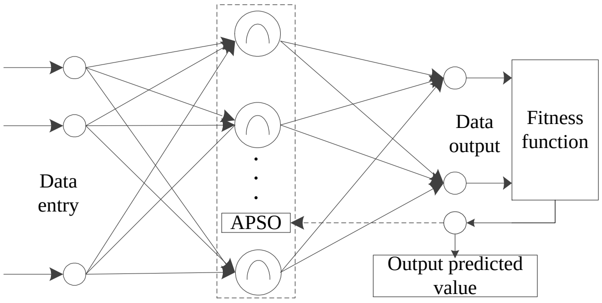

Fig.2. Adaptive Particle Swarm Optimization Steps

The input node passes the input signal to the implicit layer and the k-th network output of the output layer is

$$\hat{y}_k = \sum_{i=1}^{m} w_{ik} R_i(X), k = 1,\ldots, p \tag{9}$$

In (9) where *n* is the number of nodes in the input layer; *m* is the number of nodes in the implicit layer,*p* is the number of nodes in the output layer; $R_i(X)$ is the action function of the *i*-th node in the implicit layer

$$R_i(X) = \exp\left(\frac{-\|X - C_i\|^2}{2\sigma_i^2}\right), i = 1,\ldots, m \tag{10}$$

In (10) where *X* is the n-dimensional input vector; C_i is the center of the *i*-th basis function, σ_i is the width of the *i*-th basis function; and *m* is the number of nodes in the hidden layer.

III. APSO-RRBF BASED STOCK PREDICTION

Particle Swarm Optimization Recurrent Radial Basis Network (APSO-RRBF) can extract the hidden parameter features, correlate the sample stock data with the validated stock data, and have higher computational accuracy compared to interpolation.

Step1.Stock data input. Update the stock data under the Sig function excitation, and use the RBF iteration number as the current position parameter of the particle swarm and the fitness function as the target position.

Step2.Overlay prediction calculation. When the stock is input, the output is updated with a sliding window to compute the fitness function until the computation stops at the demand value, and the relative fitness is computed by comparing the predicted and computed values.

Step3.Data memorization and data screening. Utilizing the PSO-RBF controllable classification, the predicted sequence of output stocks is updated.

Step4.Add the test function. In this paper, we use the indicator test of M-K nonparametric statistics, and then we get a stock prediction sequence after cyclic calculation with Step 2 and Step 3, and calculate the stock sequence of other demands.

IV. STOCK TRADING DECISION MODEL

The trading decision includes buying, holding and selling of multiple stocks. In this paper, the correlation and prediction values are obtained from the objective data as part of the decision making, and the trading decision model is built by combining the latent factor score function, with different sub-models assigning different weights.

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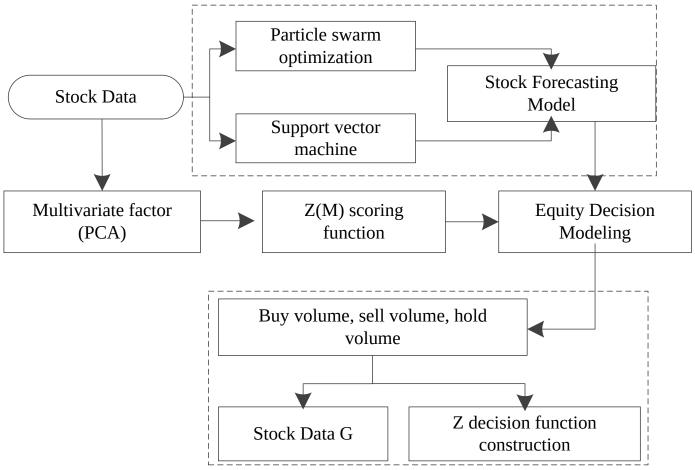

Fig.3. Trading Decision Model

Let the initial capital be A_1, then the capital after trading (k-1) back is A_k. Using the stock data at point *k* as the price of holding the stock, the return can be computed as follows

$$R_{ik} = (A_k - A_1) + \sum_{i=1}^{n} \left(H_{ij} P_{ik} \right) = \left(A_k - A_1 \right) + \sum_{i=1}^{n} \left(S_{ij} P_{ik} - B_{ij} P_{ik} \right) \tag{11}$$

The decision objective of the model is to reach a great value of the return, then there are

$$\begin{cases} \max \left\{ R_{ik} \middle| (A_k - A_1) + \sum_{i=1}^{n} H_{ij} P_{ik} \right\} \\ 0 \le H_{ij} \le 0.1 A_1 \\ \min \left\{ \psi \left(k'_{ij} \varphi \left(\sum_{i=1}^{9} k_{ij} M_i \right) \right) - \left(G_{i(j+1)} - G_{ij} \right) \right\} \end{cases} \tag{12}$$

where the update function for the holdings is

$$H_{ij} = H_{i(j-1)} - B_{ij} G_{ij} + S_{ij} G_{ij} \tag{13}$$

We compute the holdings after the trade, using the price at point j as the computed price of the funds held. The Z(M) scoring function and the functional equations for the buy and sell quantities are constructed

$$\begin{cases} B_{ij} = k_1 \log \dfrac{Z_{ij}}{n} ; Z_{ij} \ge \bar{Z} \\ S_{ij} = k_2 \dfrac{e^{Z_{ij}} - e^{-Z_{ij}}}{n} ; Z_{ij} < \bar{Z} \end{cases} \tag{14}$$

Functional Construction of Forecast Sequences and Buying and Selling Volumes

$$\begin{cases} B'_{ij} = k_3 \left(G_{i(j+1)} - G_{ij} \right) ; G_{i(j+1)} \ge G_{ij} \\ S'_{ij} = k_4 \left(G_{i(j+1)} - G_{ij} \right) ; G_{i(j+1)} < G_{ij} \end{cases} \tag{15}$$

The return function of the stock trading decision model can be obtained as

$$\begin{aligned} R_{ik} = {} & \sum_{i=1}^{n} (H_{ij} P_{ik}) + \sum_{i=1}^{n} \left(k_2 \frac{e^{Z_{ij}} - e^{-Z_{ij}}}{n} P_{ij} \right) + \sum_{i=1}^{n} \left(k_4 \left(G'_{i(j+1)} - G_{ij} \right) \right) - \sum_{i=1}^{n} \left(k_1 \log \frac{Z_{ij}}{n} \right) \\ & - \sum_{i=1}^{n} \left(k_3 \left(G'_{i(j+1)} - G_{ij} \right) \right) - A_1 \end{aligned} \tag{16}$$

V. TEST VALIDATION

Sliding window length L value and velocity spread value. In (2) and (3) can be seen, when the sample sequence to meet the fitness function after the output of the L value and speed spread, this paper is based on the stock sample sequence by particle swarm algorithm iterative calculation of the mean value, the initial value is set to 10, the flight factor are 1.5, the flight speed of the flight of the speed of 0.8, the upper limit of the number of iterations is 3000.

Based on the C-support vector machine in which stock classes with similar features are selected, stock prices for 16 days as shown in Table 1 are arbitrarily extracted, of which 13 days are used as training data and the remaining 3 days of data are used as the prediction validation set, which are substituted into the APSO-RRBF model. Combine the stock prediction results on the training set, where the horizontal coordinate demonstrates the time variation and the vertical coordinate indicates the price of the stock prediction.

Table 1 Selected stock data

Number	Stock 1	Stock 2	Stock 3	Stock 4
No.1	19.549	2.2806	5.8441	2.7942
No.2	21.143	2.3208	6.4878	2.9083
No.3	21.847	2.3544	6.4498	2.7804
No.4	21.641	2.1681	6.7678	2.7446
No.5	20.901	2.1001	6.6014	2.5753
No.6	20.841	2.2104	6.5655	2.5959
No.7	20.050	2.2252	6.5279	2.5889
No.8	20.181	2.2200	6.5831	2.9292
No.9	19.187	2.2573	6.4499	2.7502
No.10	17.382	2.1984	6.2823	2.6258
No.11	16.093	2.1123	5.9741	2.4741
No.12	17.424	2.1593	6.2062	2.6520
No.13	18.591	2.24086	6.2698	2.5515
No.14	21.162	2.2558	6.6539	2.5804
No.15	20.850	2.2473	6.2415	2.5015
No.16	20.447	2.2202	6.5197	2.4238

Table 2 shows the predicted data and the results of adaptation calculations, which shows that most of the predicted adaptations of the stocks are higher than 95%, and some of the stocks have adaptations of more than 90%.

Table 2 Selected stock data

	Stock 1	Stock 2	Stock 3	Stock 4
training set	19.549	2.2806	5.8441	2.7942
	21.143	2.3208	6.4878	2.9083
	21.847	2.3544	6.4498	2.7804
	21.641	2.1681	6.7678	2.7446
	20.901	2.1001	6.6014	2.5753
	20.841	2.2104	6.5655	2.5959
	20.050	2.2252	6.5279	2.5889
	20.181	2.2200	6.5831	2.9292
	19.187	2.2573	6.4499	2.7502
	17.382	2.1984	6.2823	2.6258
	16.093	2.1123	5.9741	2.4741
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	18.591	2.24086	6.2698	2.5515
test proof collect	21.162	2.2558	6.6539	2.5804
	20.850	2.2473	6.2415	2.5015
	20.447	2.2202	6.5197	2.4238

Fig. 4 gives the fitness of the real and predicted data for stocks and it can be seen that the fitness of stock 2, stock 3 and stock 4 is around 95% while the predicted fitness of stock 1 is around 90%.

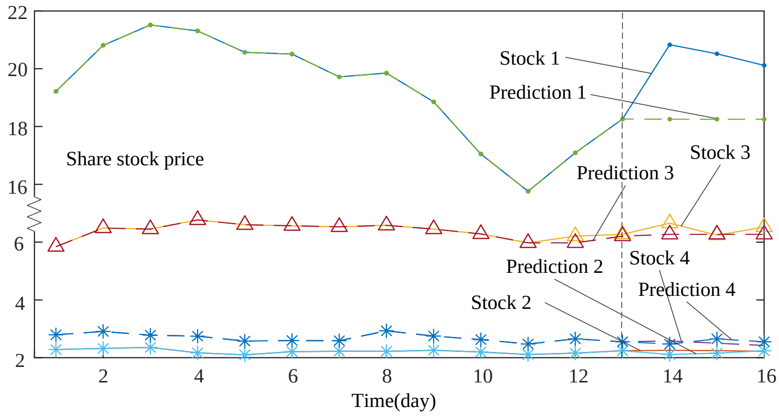

Fig.4. Stock Forecast Results

With the data collected on day 13, the stocks are predicted from day 14 to day 16, assuming that the investment capital on day 1 is \$2,000, and the prediction shows that stock 1, stock 2, and stock 4 are losses in this interval, so only stock 3 is purchased. the amount of stock held by the purchaser for the first purchase is 0, and the holding of the stock is subject to a management fee of \$1/day, and the gain to loss ratio is calculated by the prediction model, and the decision The objective is to reach a great value of return, and the return function of the stock is known to be

$$R_{i(k+1)} = \sum_{i=1}^{n}\left(k_2 \frac{e^{Z_{ij}} - e^{-Z_{ij}}}{n} P_{ij}\right) + \sum_{i=1}^{n}\left(k_4\left(G'_{i(j+1)} - G_{ij}\right)\right) + \sum_{i=1}^{n}(H_{ij}P_{ik}) + -\sum_{i=1}^{n}\left(k_1 \log\frac{Z_{ij}}{n}\right) \\ -\sum_{i=1}^{n}\left(k_3\left(G'_{i(j+1)} - G_{ij}\right)\right) - A_1 \tag{17}$$

For example, stock 3 was purchased on day 1 for \$5.85 and sold on day 16 for \$6.27, with a real value of \$6.65, and a gain on the purchase of 300 shares of

$$R_{14} = (A_{16} - A_1) + \sum_{i=1}^{15}\left(H_{ij}P_{ik}\right) = \left(A_{16} - A_1\right) + \sum_{i=1}^{15}\left(S_{ij}P_{ik} - B_{ij}P_{ik}\right) = 229.9799 \tag{18}$$

Define the earnings ratio S as

$$S = \sum_{i=1}^{n} R / \sum_{i=1}^{n} B_i \tag{19}$$

Calculated cost of \$2000 can gain \$229.99, the gain percentage is 11.45%, indicating that the model has better profitability and feasibility, can provide a better reference value for the optimization of stock portfolio decision-making problem.

VI. CONCLUSIONS

In this paper, based on the regularity and predictability of stocks, the index factor for stock classification is obtained by C-support vector machine, and then combined with the adaptive particle swarm optimization of recurrent radial basis network algorithm to predict new stock data, which gives the trading strategy of buying, selling and holding multiple stocks, providing a better solution for the optimal decision-making problem of stock investment portfolio.

In order to further optimize the decision-making model, the next step of this paper is to improve the support vector machine classification algorithm based on the intrinsic correlation between different stocks by using K-Means grey clustering to obtain several stocks with higher feature identity as a new stock cluster. After that, several stock clusters with higher maturity are extracted, and the potential factors for stock decision-making are obtained through multivariate analysis, and then the new stock trends are predicted by the particle swarm-improved ARBF, which provides a better solution for the stock decision-making problem.

VII. ACKNOWLEDGEMENTS

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