Building a Broad Asset Class Allocation Strategy Based on RBF Neural Networks

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Abstract—Globally, there is an industry consensus on broad asset class allocation as a core investment approach. This paper gives investment strategies for several major asset classes and predicts the future state of China's economy through macroeconomic models, which will play a role in guiding the future development of China's economy. According to the problem studied in this paper we construct a time series forecasting model based on quadratic exponential methods, which takes the historical data of indicator data as input, derives the law based on time series changes, and finally realizes the simulation of China's economic growth, inflation, and interest rates in the next five years. We substitute the composite economic evaluation value into the quadratic exponential methods time series forecasting model to forecast the data for the next five years, based on the trend of the data to conclude that the economic state is in a high growth period in 2022-2024; The state of the economy is in a period of medium growth in 2025-2026. And then based on the model analysis of the strategy research, this study has an important role and research significance in the re-financing industry.

Keywords- Asset Allocation; Quadratic exponentialmethods; RBF neural network; Correlation Analysis

1. INTRODUCTION

Globally, there is an industry consensus on broad asset class allocation as a core investment approach. The "broad asset classes" represent clusters of assets with similar characteristics, and "allocation" is the distribution of investment funds among different asset classes according to investment needs. The fundamental idea of broad asset class allocation is not to put all investments on one macro indicator, but to dynamically adjust the portfolio of investments according to the trend of various macro indicators. Broad asset class allocation smooth portfolio risk for investors through diversification compared to stand-alone assets. In this sense, broad asset class allocation is a tool with natural risk control advantages.

ICBBEM 2023, May 19-21, Hangzhou, People's Republic of China

DOI 10.4108/eai.19-5-2023.2334216

2. MODEL CONSTRUCTION AND SOLVING

We construct a time series forecasting model based on quadratic exponential methods in order to simulate macro factors such as economic growth, inflation, and interest rates in China for the next five years [1]. The model derives a law based on time series changes by taking historical data of indicator data as input, and finally achieves a smoothed forecast of future data. To illustrate the state of the economy that China will face in the next five years, we substitute the composite economic evaluation value derived from question 1 into a quadratic exponential methods time series forecasting model to forecast the data for the next five years and derive the state of the economy based on the trend of the data. The flow chart for solving this problem is shown in Figure 1 [2].

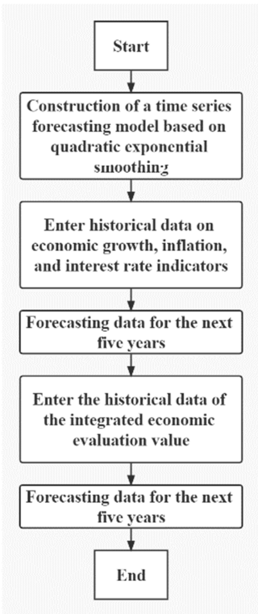

Figure 1. Flow chart of the solution

2.1 Construction of a time series forecasting model with quadratic exponentialmethods

The one-time exponential methods method overcomes the disadvantages of the moving average method though. However, when there is a linear trend in the movements of the time series, forecasting by primary exponential methods still suffers from significant lagged bias. Therefore, it must also be corrected. The correction is done in the same way as the trend moving average method, i.e., quadratic exponential methods is then done to create a linear trend model using the law of lagged deviation. This is the quadratic exponential methods method. It is calculated as[2]:

$$S_t^{(2)} = \alpha S_t^{(1)} + (1-\alpha) S_{t-1}^{(2)} \tag{1}$$

Among them: $S_t^{(2)}$ is the quadratic exponential methods value, t is the number of periods from t to the forecast period; when the time series$\{y_t\}$, When there is a linear trend starting from a certain period, similar to the trend moving average method, a linear trend model can be used to forecast [3]:

$$\hat{y}_{t+T} = a_t + b_t T, T = 1,2, \tag{2}$$

$$s.t. \begin{cases} a_t = 2S_t^{(1)} - S_t^{(2)} \\ b_t = \frac{\alpha}{1-\alpha}(S_t^{(1)} - S_t^{(2)}) \end{cases} \tag{3}$$

Among them: t is the number of current periods; t is the number of periods from t to the forecast period; a_t is the intercept distance; b_t is the slope, both of which are also known as methods coefficients [3].

2.2 Solving a time series forecasting model with quadratic exponentialmethods

We use the price index as the fundamental determinant of economic inflation. When the price index increases, it represents economic inflation, and when it increases anyway, it represents economic contraction [4]. The data of the four indicators of national economic accounting, price index, interest rate exchange rate and comprehensive economic evaluation value from 2001 to 2021 are substituted into the model for calculation, and finally the data forecast of the four indicators for the next five years is realized [5], and the forecast results are shown as follows pictures:

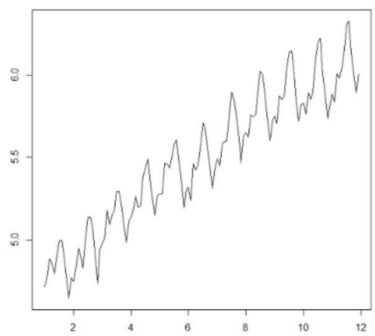

Figure 2. One exponentialmethods sequence

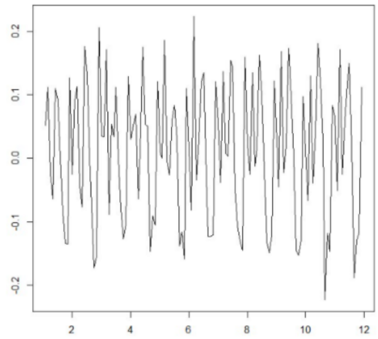

Figure 3. Quadratic exponentialmethods series

As seen in Figure 2, the series is not yet smooth, and the result of doing a Log methods and then a difference is shown in Figure 3. We found that the sequences after methods by quadratic exponential can be used to do prediction, so our prediction results are shown in Figure 4 (due to the large amount of data, only some prediction results pictures of some sequences are shown) The trend model for development as show in Figure 4.

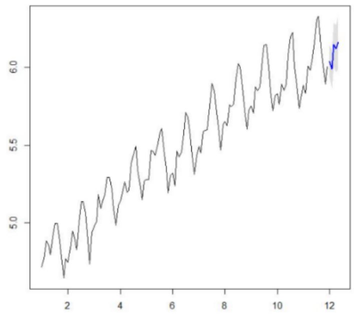

Figure 4. Partial forecast results

We finally derived the forecast data for the next five years for the four indicators of national accounting, price index, interest rate exchange rate and comprehensive economic evaluation value, as shown in Table 1.

TABLE I. FORECAST DATA FOR THE NEXT 5 YEARS FOR THE FOUR INDICATORS

Time	Comprehensive economic evaluation value	National Accounts	Price Index	Interest Rate Exchange Rate
2022	1216.569	1228735.094	101.354	2.439
2023	1302.976	1316005.760	99.349	2.469
2024	1426.312	1440575.120	102.649	2.764
2025	1507.756	1522833.560	103.461	2.572
2026	1598.264	1614246.640	104.126	2.415

3. CONSTRUCTION OF RBF NEURAL NETWORK PREDICTION MODEL

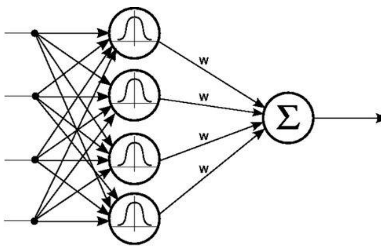

Figure 5. RBF neural network principle

RBF network training: the purpose of training is to find the final weights of the two layersC_j,$D_j$andW_j.

The training process is divided into two steps: the first step is unsupervised learning [7], training to determine the weights between the input layer and the hidden layerC_j,D_j; The second step is supervised learning [8], where training determines the weights between the implicit layer and the output layerW_j.

The centers of different hidden layer neurons should have different values, and the corresponding widths to the centers can be adjusted so that different input information features can be maximally reflected by different hidden layer neurons [7]. The initial values of the central parameters of the RBF neural network are:

$$c_{ij} = min\, i + \frac{max\, i - min\, i}{2p} + (j-1)\frac{max\, i - min\, i}{p} \tag{4}$$

p is the total number of neurons in the hidden layer, $j = 1,2,\ldots,p$; $min\, i$ is the minimum value of all input information of the i-th feature in the training set, maxi is the maximum value of all input information of the i-th feature in the training set.

$$D_j = \left[d_{j1}, d_{j2}, \cdots, d_{jn}\right] \tag{5}$$

The width vector affects the range of action of the neuron on the input information: the smaller the width, the narrower the shape of the action function of the corresponding hidden layer neuron, and then the smaller the response of information that lies near the center of other neurons out of that neuron.

Calculation method:

$$d_{ji} = d_f\sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(x_i^k - c_{ji}\right)} \tag{6}$$

Where: d_f is the width adjustment coefficient, which takes a value less than 1. The effect is to make it easier for each hidden layer neuron to achieve the ability to perceive local information, which helps to improve the local response of the RBF neural network [4].

3.1 Determining radial basis neural network transfer parameters

The radial basis network transfer function is based on the distance $|X - C_j|$ between the input vector and the threshold vector as the independent variable. where $|X - C_j|$ is obtained by the product of the input vector and the row vector of the weighted matrix C. The radial basis neural network transfer parameters can take many forms.

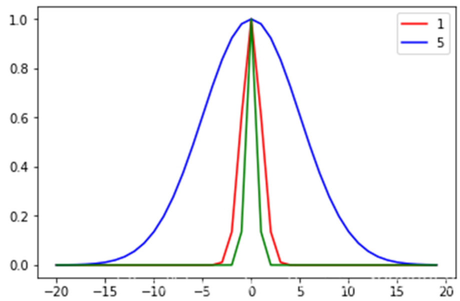

Figure 6. Gaussian radial basis function principle

When the input vector is added, each neuron in the radial base outputs a value representing the proximity between the input vector and the neuron weight vector. If the input vector differs a lot about the weight vector, the radial base output is close to 0; If the input vector is close to the weight vector, the output of the radial base layer is close to 1. Solution of RBF neural network prediction model

According to the characteristics of the data in this paper, the input nodes of our model are 5, the central node is 3, and the output node is 1. We substitute the data into the RBF neural network for training, and the results are shown in Figure 7.

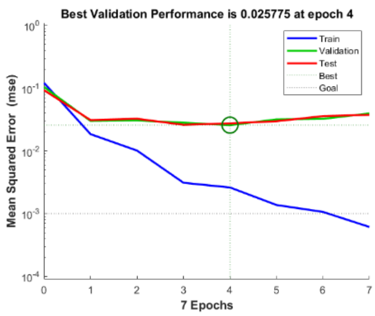

Figure 7. BP neural network training error

With the above training results, it is known that the training error is 0.026, so the accuracy of neural network training is good. We finally predict the data of risk-return characteristics for various economic states as shown in the table below [9].

TABLE II. RISK-RETURN CHARACTERISTICS OF CSI 300

Risk-return characteristics	Smoothing period	Low growth period	Medium growth period	High growth period
Expected revenue	4432.6140	4489.6210	4492.3970	4513.6150
Yield standard deviation	0.0420	0.0580	0.0870	0.1240
Sharpe Ratio	0.3890	0.5680	0.7590	0.8940

TABLE III. RISK-RETURN CHARACTERISTICS OF THE S&P GOLDMAN SACHS COMMODITY TOTAL RETURN INDEX

Risk-return characteristics	Smoothing period	Low growth period	Medium growth period	High growth period
Expected revenue	3579.3180	3698.9460	3967.3420	4192.1160
Yield standard deviation	0.0433	0.0597	0.0896	0.1277
Sharpe Ratio	0.4007	0.5850	0.7818	0.9208

TABLE IV. RISK-RETURN CHARACTERISTICS OF CHINA BOND-COMBINED WEALTH (3-5 YEARS) INDEX

Risk-return characteristics	Smoothing period	Low growth period	Medium growth period	High growth period
Expected revenue	224.8940	225.4260	225.6870	225.9640
Yield standard deviation	0.0436	0.0603	0.0904	0.1289
Sharpe Ratio	0.4043	0.5903	0.7888	0.9291

TABLE V. RISK-RETURN CHARACTERISTICS OF MONEY FUNDS

Risk-return characteristics	Smoothing period	Low growth period	Medium growth period	High growth period
Expected revenue	1635.4985	1635.6420	1635.8460	1636.0180
Yield standard deviation	0.0430	0.0594	0.0891	0.1269
Sharpe Ratio	0.3982	0.5815	0.7770	0.9152

5. CONCLUSIONS

RBF neural networks have strong nonlinear fitting ability, can map arbitrarily complex nonlinear relationships, and the learning rules are simple and easy to implement by computer. With strong robustness, memory capability, nonlinear mapping capability [10], and powerful self-learning capability, there is a large market for applications. RBF neural network is a feed-forward neural network with excellent performance. RBF network can approximate any nonlinear function with arbitrary accuracy and has global approximation capability. However, the model has certain shortcomings: 1. It is not possible to ask the necessary questions to the user and the neural network cannot work when the data is not sufficient; 2. Turning all problem characteristics into numbers and all reasoning into numerical calculations inevitably results in loss of information.

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