Time series neural network systems in stock index forecasting

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Abstract

This paper adopts artificial neural network (ANN) and two varieties of time series neural network to forecast the stock index of Chinese market. Daily close prices between 1999 and 2011 are tested. The ANN works as a benchmark. Its inputs include delayed price and technical indicators. Time series neural network with external input (NARX) outperforms the Time series neural network (NAR), and it works best when the delay is 8. Moreover, NARX has the best ability of the three. This is mainly resulted from the fact that it contains external data and the technical indicators while NAR does not. As a whole, the ANN and NARX models achieved satisfying results. They can be employed by practitioners to assist trading and by regulators for monitoring. The NARX will be improved when more external data imported.

Keywords: forecasting, ANN, NAR, NARX

1 Introduction

China is the second biggest and the fastest growing economy in the world now. However Chinese financial markets are still under developed. There are two stock exchanges in Shanghai and Shenzhen respectively. And two distinct kinds of common stocks: A shares and B shares. In early times, Chinese investors could only trade A shares, and B shares are traded in U.S. dollars and H.K. dollars by foreign investors. The mechanism of the markets have many aspects need be improved, such as the lack of short trading and T+0 transactions is not supported. Moreover, inside information trade, financial fraud and the frequently changing policies cause fluctuations and jumps. The Chinese stock market is still not an ideal and stable investment channel, especially for the uninformed and retail investors. However, these characteristics of instability may provide a lot of researchable opportunities.

This paper is motivated by the fact that many investors in China make significant profits in predicting the stock markets. Generally, there are two types of practitioners who survive in the market: fundamental analysts and technical analysts. Fundamental analysts are more interested in the general policies, market information and companies' financial statements. However, technical analysis makes use of the historical data to build a model, which can predict the future price. Academic researchers are more interested in technical analysis for its easiness to be described by mathematical equations.

Many existing theories support the classical efficient market hypothesis (EMH) according to which the current price of the market already fully reflects the overall information. Any imbalance should be detected and diminished immediately [1]. Most developed markets prove the EMH theory holds [2-4]. However, there are still many technical analysts who make profit in the market. This paper also reported the Chinese market is analyzable which may challenge the weak form of the EHM.

Artificial Neural Networks is a mostly used classifier which can also be utilized for prediction. There exist vast literatures, which used ANN to predict the price return and the direction of its movement. ANN and its varieties have been demonstrated to provide promising outcome in the stock price prediction.

2 Literature review

In recent years, there have been a growing number of researches intending to capture the movements of various financial instruments. Tremendous efforts have been made to build models to describe and predict the price path. In the following section, we focus the review of the previous studies on ANN and its varieties' application in financial fields.

There exist vast literatures, which used ANN to predict the price return and the direction of its movement. ANN has been demonstrated to provide promising outcome in the stock price prediction. White [5] used Neural Networks to forecast the market first. He found the model were profitable for IBM common stock. Chiang [6] used ANN to forecast mutual funds. Some variations were later introduced. The probabilistic neural network is used to fit return directions. PNN is proved to outperform the GMM with random walk and Kalman filter [7]. Altay and Satman [8] tested the performances of ANN to predict the ISE-30 and ISE-All Indexes. The result shows that the ANN is better and OLS regression. Chinese market also draws some scholars' interest. Cao Leggio and Schniederjans [9] demonstrated the ANN outperformed the CAPM and Fama and French's 3-factor model in the empirical research about Shanghai Stock Exchange.

Many researchers tend to combine several pattern recognition techniques to improve the prediction model. Tsaih, Hus and Lai's [10] research indicate that the reasoning neural networks outperform the back propagation networks and perceptron.

However, ANN's application in stock prediction may has many flaws. Romahi Shen found ANN occasionally suffers from the over fitting problem.

3 Data description

Our data is collected from every trading day since the establishment of the exchange. The price used in the empirical study is the closing price of Shanghai Stock Exchange. Although there are two exchanges in China, Shanghai and Shenzhen, and no stock is allowed to be listed in both exchanges. However, Chinese policy makers show a strong inclination to develop Shanghai exchange as a main market and make Shenzhen exchange to be a growing enterprise market. Therefore the Shanghai exchange takes most part of the total market value, and Chinese investors and media always use Shanghai Composite Index as the main indicator. This paper also chooses Shanghai exchange's data by convention.

There are 5118 trading days from 1900 to 2011. Daily closing price is chose as the sample data. Figure 1 presents the whole data's pattern.

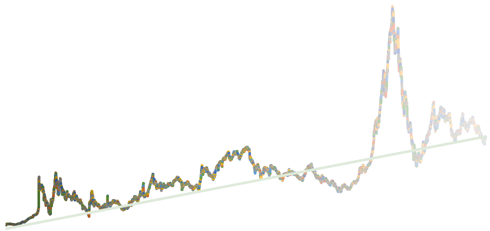

FIGURE 1 Shanghai composite index movement, 1990-2011

As shown in Figure 1, in the last twenty years, Chinese stock market did not grow as fast as its economy. The investors suffered a really long bear market in the first 15 years. Many scholars and practitioners put the blame on the imperfection of the institutional system. However, in 2007 the stock index tripled in less than a year. But the prosperity did not last long, it soon returned to 2006's level in 2008 due to the influence of American subprime mortgage crisis. Some experts claimed that the rapid up and down brought even greater damage to the market than the everlasting bear market before. In the post crisis period from 2008 to 2011, the stock market was not stable yet. Panics strike the market after rumors and news. In general, after more than twenty years development, the Chinese stock market is still fragile and instable.

The Figure 2 is the daily return of the Shanghai stock index, and many spikes are observed in the return plots, which means the market has a fat tail.

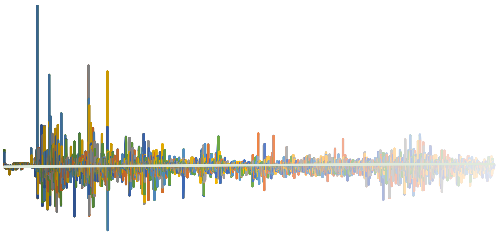

FIGURE 2 Daily return of the Shanghai composite index

Table 1 summarizes the common statistics of the daily return. The positive skewness of 5.37 indicates the data have a fat tail and high peak, which complies with the feature of most financial markets. The kurtosis is 140.55, which means the data is highly non-normally distributed. The Jarque-Bera normality test also rejects the hypothesis of normal distribution. The Arch test accepts that there is relation between the squared return and its one step lag. Finally, the L-B test shows autocorrelation of one, two and three steps all exist, which allow us to model the mean price movement with MA.

TABLE 1 Sample statistics of the Shanghai stock index daily return

Statistics	Estimate
Mean	0.0074
Maximum	0.312324
Minimum	-0.07776
Standard deviation	4.373974
Skewness	5.373978
Kurtosis	140.5569
Jarque-Bera normality test(lags=1)	p=0.001
ARCH test (lags=1)	p=0.1199
Ljung-Box autocorrelation test (lags=1,2,3)	p=0.001, 0.0295,0.0014

4 Prediction models

4.1 ARTIFICIAL NEURAL NETWORK

The ANN model is a two-layer BP network with single sigmoid hidden layer, which can be described by Equation (1) and Figure 3. The output neurons are linear. The network is feed-forward which can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough hidden neurons. The network is trained with Levenberg-Marquardt back propagation algorithm. The ANN are represented by Equations (2)-(7).

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

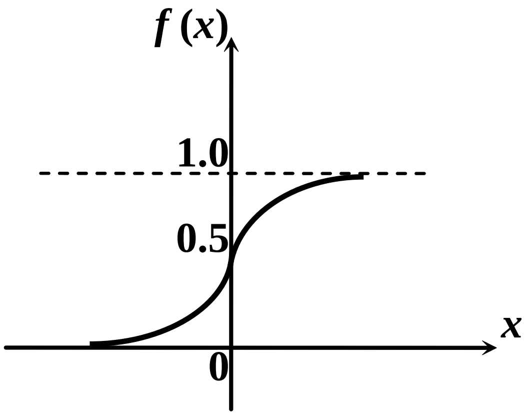

FIGURE 3 Sigmoid function

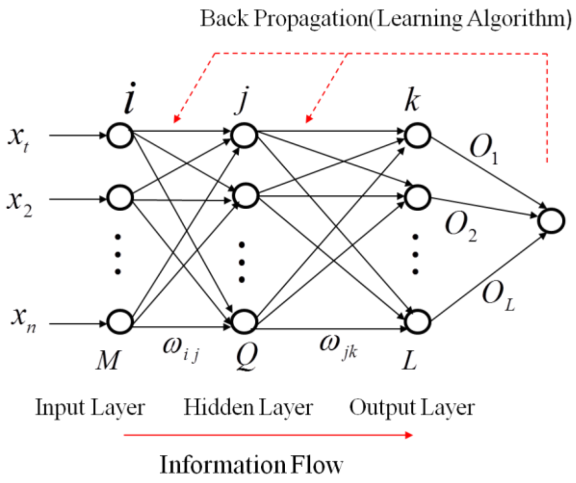

FIGURE 4 Network structure of ANN model

Hidden Layer:
Input:

$$net_j = \sum_{i=0}^{n} \omega_{ij} x_i \tag{2}$$

Output:

$$f(net_j) = \frac{1}{1+e^{-net_j}} \tag{3}$$

Weight adjustment

$$\Delta w_{jk} = \eta \delta_k y_j = \eta (d_k - o_k) o_k (1 - o_k) y_j \tag{4}$$

Output Layer:
Input:

$$net_k = \sum_{j=0}^{m} w_{jk} y_j \tag{5}$$

Output:

$$o_k = f(net_k) \tag{6}$$

Weight adjustment

$$\Delta \omega_{ij} = \eta \delta_j x_i = \eta (\sum_{k=1}^{L} \delta_k w_{jk}) y_j (1 - y_j) x_i \tag{7}$$

How to select the input data is the key issue for the neural network. We use the present day and 3 earlier days' index as original data. We also use some technical indicators which are commonly used by practitioners. The indicators include Moving average convergence divergence (MACD), Price rate of change (PRC), Acceleration between times (ABT), Momentum between times (MBT), Relative strength index (RSI). There are 9 inputs for the network input in total.

TABLE 2 Technical indicators used in the ANN model

MACD	Moving averages of different time frames which indicate momentum changes and swings in the mood of the crowd, to give buying and selling signals that catches the big moves.
PRC	Percentage change between the most recent price and the price n periods in the past.
ABT	Difference of two momentums separated by some number of periods.
MBT	Difference between two prices (data points) separated by a number of times.
RSI	Recent performance of a security in relation to its own price history

4.2 TIME SERIES NEURAL NETWORK – NONLINEAR AUTOREGRESSIVE (NAR)

Prediction is a kind of dynamic filtering, in which past values of one or more time series are used to predict future values. Dynamic neural networks, which include tapped delay lines are used for nonlinear filtering and prediction.

There are many applications for prediction. For example, a financial analyst might want to predict the future value of a stock, bond or other financial instrument. An engineer might want to predict the impending failure of a jet engine.

Predictive models are also used for system identification (or dynamic modelling), in which you build dynamic models of physical systems. These dynamic models are important for analysis, simulation, monitoring and control of a variety of systems, including manufacturing systems, chemical processes, robotics and aerospace systems.

The time series neural network uses past prediction as input. Unlike the classic ARMA model, the time series neural network depicts the nonlinear autoregressive features of the series. And this model can rely on just the index data. No other technical indicators and information are needed.

$$y(t) = f(y(t-1), \ldots y(t-d), x(t)) \tag{8}$$

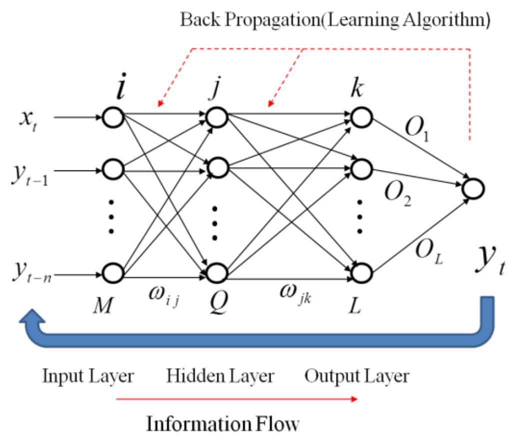

FIGURE 5 Network structure of NAR model

4.3 TIME SERIES NEURAL NETWORK WITH EXTERNAL INPUT-NARX

The NARX is an improved model of NAR. It can include information besides price to better the prediction. For example, in financial market some indicators like trade volume can be introduced. However, unlike the single stock data, our stock index does not include these information. Therefore, we use the technical indicators as input data. We also import the same indicators, which are used in the ANN model before.

$$y(t) = f(x(t-1),\cdots x(t-d), y(t-1),\cdots y(t-d), x_{1,t}, x_{2,t}) \qquad (9)$$

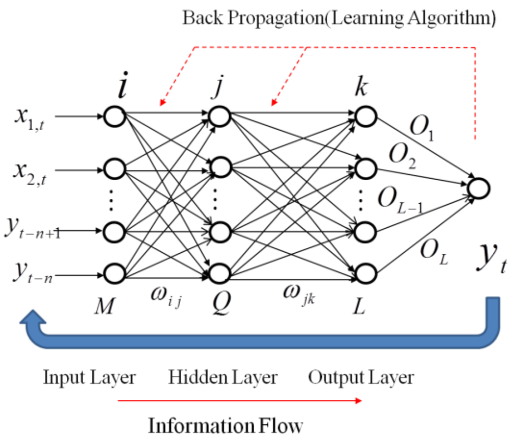

FIGURE 6 Network structure of NARX model

Both NAR and NARX networks will be trained with Levenberg-Marquardt back propagation algorithm.

5 Results and analysis

The 5118 trading days' close index are divided into three parts randomly. 70% are used to train the network, 15% are used to validate the training network, which could stop iteration when the validation result is convergence. The final 15% data are employed to test the predictive ability of the trained model. All the data are pre-treated to adapt for the sigmoid function. Therefore the inputs are standard normalized between 0 and 1.

TABLE 3 Prediction results of 3 neural network models

	MSE	R
ANN	1633	9.992616
NARX delay 1	1549	9.992736
NARX delay 2	1533	9.992814
NARX delay 3	1522	9.992920
NARX delay 5	1513	9.992883
NARX delay 7	1478	9.992896
NARX delay 8	1463	9.992905
NARX delay 9	1498	9.992891
NARX delay 14	1738	9.991821
NAR delay 1	1558	9.992778
NAR delay 2	1735	9.991892
NAR delay 3	1979	9.990803
NAR delay 5	4861	9.977734
NAR delay 7	5074	9.975614
NAR delay 14	6566	9.970092

As can be seen in the result table, NARX outperforms ANN and NAR NARX performs best when delay is set 8. This means 8 earlier days' prediction is meaningful to future prediction. When the delay is larger than 8, It will cause over fit issue which make the trained network less adaptable. However, the NARX's performance indicates the external data is useful. This may result in the external data are mainly technical indicators, which are generated by the stock index and proved to be useful by practitioners. And when delay is longer, the NAR works worse.

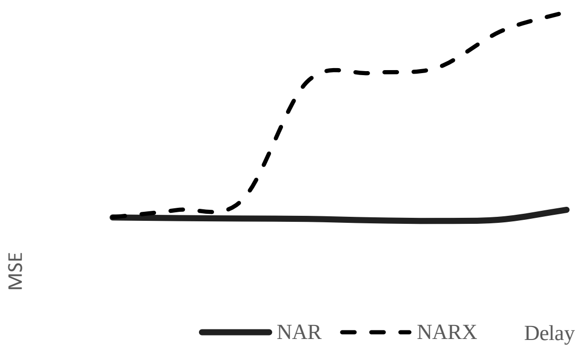

FIGURE 7 MSE of NAR and NARX with different delays

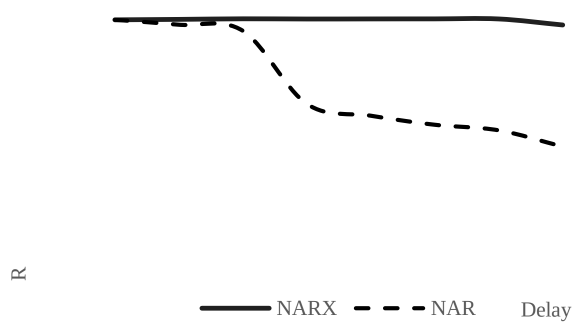

FIGURE 8 Prediction Relative Index of NAR and NARX with different delays

6 Conclusion

It is shown that the neural network models established in this research has several advantages such as high prediction accuracy and quick convergence speed. The basic ANN model work moderately which is used as a benchmark in this paper. Two varieties of the time series neural network are introduced: Nonlinear Autoregressive (NAR) and Nonlinear Autoregressive with external data (NARX). NARX model works much better than the ANN model, and it work best when the delay is set 8. NAR works less accurate than NARX and ANN since we use technical indicators as external data. The result shows that the model can be applied for analyzing the stock market, which is useful for practitioners and regulators. If more external data were imported, the NARX model will produce a better result.

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