A Stock Market Forecasting Model Based on Adaptive Neuro-Fuzzy Inference Systems

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Abstract—The price variation of stock market is a dynamic system and the chaotic behavior of the stock price movement duplicates complication of the price prediction. A challenging and daunting task for financial investors is determining stock market timing - when to buy, sell and the future price of a stock. This challenge is due to the complexity of the stock market. The automated computer programs using data mining and forecast technologies do a fare amount of trades in the markets. Data mining is well founded on the theory that the historic data holds the essential memory for forecasting the future direction. This technology is designed to help investors discover hidden patterns from the historic data that have probable forecasting capability in their investment decisions. Different methods have emerged that increase the accuracy of stock forecasting. Examples of these methods are Fuzzy logic, Neural Network and hybridized methods such as hybrid Kohonen Self Organizing Map (SOM), Adaptive Neuro-Fuzzy Inference System (ANFIS) etc. In our purposed prediction methods uses different learning algorithms techniques to forecast stock market trading. The forecasting system achieved accurate predictions and the simulation on stocks trading showed an excellent profit.

Keywords—ANFIS, ANN, FLANN, BP, SOM.

I. INTRODUCTION

Traditionally the investment community accepts two major theories: the Firm Foundation and the Castles in the Air. Reference to these theories allows us to understand how the market is shaped, or in other words how the investors think and react. It is this sequence of ‘thought and reaction’ by the investors that defines the capital allocation and thus the level of the market. The factors that are under discussion on this schema are: the content of the ‘Information’ component and the way that the ‘Investor’ reacts when having this information. Price fluctuation of stock marker is not only restrained by the relation between supply and demand, but also impacted by some external factors such as politics, policy and fluctuation of foreign stock markets, which brings much trouble to the simulation and forecasting of financial signal. How to improve the forecasting accuracy of financial signals has become an important subject in financial engineering field. Research on forecasting model of stock price has been the focus of many scholars since stock market has been established in 19th century. Statistical forecasting models, such as AR, ARIMA and ARCH, have been applied in this area widely, but have not got ideal effect. More and more scholars recently regarded stock market as a nonlinear dynamic system in their research. Schinkman and LeBaron (1989) found that chaotic phenomena exist in daily stock returns series and weekly stock returns series [1]. Bouqata Bouchra (1997) predicted the change of market interest rate by using artificial neural network (ANN) [2]. Algis arliauskas (1999) proposed a forecasting algorithm of financial chaotic signals based on neural network [3]. Zhang Qian and Gao Liqun (2002) used wavelet noise filtering technique and least square method to forecast price of B shares in China [4]. With the development of nonlinear theory and artificial intelligent technology, wavelet analysis and neural network have become effective analysis tools in financial market, but the result is not very good when forecasting stock returns with BP network [5]. Wavelet network is the extension of feed forward networks, comparing with ANN, WNN has following advantages [6], (a) WNN has fast convergence because of the low correlation of wavelet neuron; (b) expansion and contraction factors in wavelet function make the approximation capability of network more powerful; (c) with the good partial characteristic and multi resolution learning, wavelet neural network matches commendably the signal, which can express function characteristic with different resolutions, and has higher forecast accuracy.

The paper investigates forecasting model of nonlinear financial signals based on wavelet neural network. Through simulating Shanghai stock market returns on this basis, it shows that wavelet neural network is superior to BP network when forecasting financial chaotic signals.

II. Models

II.1. BP neural network

BP (Back Propagation) neural network is a multilayer feed forward network that is trained with the error back propagation learning algorithm, which is the most popular neural network model. BP neural network can study and store a lot of mapping relationship of input-output model, and need not reveal mathematical equation that describing the mapping relationship in advance. Its learning rule is to use steepest descent method to minimize
the error square sum of network, through back propagation to continuously adjust the weights and threshold of network. Topology of BP neural network model includes input layer, hidden layer and output layer.

Figure-1 gives the j-th BP neuron (node), it simulates the most important function of biological neuron that is weighting, summation and transition. $x_i$ refers to the input of neuron i, in which the range of i is from 1 to n, $w_{ji}$ refers to the joint strength between neuron i and j, that is weights, here i has the same meaning as were ferred above; $b_j$ refers to threshold; $f(\cdot)$ refers to activation function; $y_j$ refers to the output of neuron j. $S_j$ refers to the net input value of the j-th neuron, that is

$$S_j = \sum w_{ji} x_i + b_{j}$$

Where $X = [x_1, x_2, \ldots, x_n]^T$, $W_j = [w_{j1}, w_{j2}, \ldots, w_{jn}]$

After $S_j$ through the mapping of $f(\cdot)$, the output of neuron j will be got as follows:

$$y_j = f(s_j) = f(w_{j1}x_1 + b_{j}) = \begin{cases} s_j & \text{if } s_j \geq 0 \\ s_j - 2s_j & \text{if } s_j < 0 \end{cases}$$

II.II Model improvement by Wavelet Network

Artificial Neuro-Fuzzy Inference Systems are a class of adaptive networks that are functionally equivalent to fuzzy inference systems. ANFIS represent Sugeno Tsukamoto fuzzy models. ANFIS uses a hybrid learning algorithm Logical Nebulosa fuzzy set and logic theory is one of the most prominent tools to handle uncertainty in decision-making. The major advantages of fuzzy system models are their robustness and transparency. Fuzzy system modeling achieves robustness by using fuzzy sets which incorporates imprecision to system models. In addition, unlike some system models, such as neural networks, the fuzzy system models are highly descriptive. Over the last two decades, researchers proposed several fuzzy system modeling methods that can extract the hidden rules of a system automatically by using historical data. The combination of fuzzy systems and neural networks has recently become a popular approach in engineering fields for solving problems in control, identification, prediction, pattern recognition, etc. One well known structure is the adaptive neuro-fuzzy inference system, others include self-constructing neural fuzzy inference networks based on Takagi–Sugeno–Kang (TSK) rules and fuzzy wavelet neural networks that have been used for identification and control purposes.

Back propagation algorithm is a feed forward neural network supervision algorithm. Feed forward neural network is capable to tackle complex nonlinear signals.

Feed forward neural network has a function of:

$$f : [0,1]^n \rightarrow \mathbb{R}^m$$

Neural network is able to predict time order in nonlinear by designing a neural network to fix time order without hypothesis of stability on time order.

General steps of multilayer feed forward BP neural network for prediction are:

- Determine the network structure and prediction precision, determination of input nodes number hidden layers and number of node in each layer.
- Divide sample data, including study sample data and testing sample data.
- Select appropriate algorithm to train the network, in order to fix study sample time order as much as possible.
- Use testing sample data to test training network. If the result is satisfactory this trained network can be applied to predict. Otherwise, adjust network structure, follow step 3 again till more satisfactory testing result appears.

Prediction on stock price by neural network consists of 2 steps:

- Training the neural network
- prediction

In training step network generates a group of connecting weights getting an output result through positive spread and then compares this with expected value. If the error has not reached expected minimum, it turns into negative spreading process. Prediction process is to input testing sample to predict, through stable neural network, connecting weights and threshold.
We assume the fuzzy inference system under consideration has two inputs x and y and one output z. Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno’s type.

Rule 1: If x is A1 and y is B1, then \( f_1 = p_1x + q_1y + r_1 \).

Rule 2: If x is A2 and y is B2, then \( f_2 = p_2x + q_2y + r_2 \).

The node functions in the same layer are of the same function family as described below:

Layer 1: Every node i in this layer is a square node with a node function \( O_i^1 = \mu A_i(x) \).

Layer 2: Every node in this layer is a circle node labeled Tz which multiplies the incoming signals and sends the product out. For instance,

\[ w_i = \mu A_i(x) \times \mu B_i(y), i = 1,2 \]

Layer 3: Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rule’s firing strength to the sum of all rules’ firing strengths:

\[ \frac{w_i}{w_1 + w_2}, i = 1,2 \]

Layer 4: Every node i in this layer is a square node with a node function,

\[ O_i^3(x) = \frac{w_i f_i}{w_1 \sum_i w_i f_i} = \frac{w_i p_i x + q_i y + r_i}{\sum_i w_i} \]

Layer 5: The single node in this layer is a circle node labeled C that computes the overall output as the summation of all incoming signals, i.e.,

\[ O_i^5(x) = \text{overall output} = \sum_i \frac{w_i f_i}{\sum_i w_i} \]

Hybrid Learning Algorithm

From the proposed type-3 ANFIS architecture, it is observed that given the values of premise parameters, the overall output can be expressed as a linear combinations of the consequent parameters. More precisely, the output \( f \) in can be rewritten as

\[ f = \sum_i \frac{w_i f_i}{w_1 + w_2 f_1 + w_2 f_2} = \frac{w_1 f_1}{w_1 + w_2 f_1} + \frac{w_2 f_2}{w_1 + w_2 f_1} \]

III. Analysis of a Real World Nonlinear- Nonstationary Time Series

(1) Data Patterns

The data for the experiment on stock market prediction has been collected from many stock indices namely Bombay Stock Exchange (BSE) SENSEX, International Business Machines Corp., Reliance Industries Limited (RIL), Oracle Corporation. The data are collected from January 1998 to October 2010, totaling 3242 data patterns. The data obtained from the stock market has many attributes like open, high, low, close, volume of stock traded in each day. The model which is designed to forecast is imitated to predict the closing price of the index on each day of the forecasting period.
(2) Data Normalization
The inputs are normalized in a range from 0.1 to 1 for the network to function properly. One of the standard techniques of normalization is used here. It is used to express the actual value in terms of minimum and maximum value of the data set.

\[ u = \left( \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \right) \times (1 - 0.1) + 0.1 \]

Where, \( u \) and \( x \) represents normalized and actual value respectively.

(3) Training and Testing Process
Each input pattern normalized and given to the network prior to the network training. The weight vector of the network initially set to random values between -1 to 1. The input pattern and weight applied to the network. The network response i.e. output is compared with desired output, their respective error stored and each weight for every path is update using adaptive learning algorithm. Based on error, network modifies its weight to improve the network response. Network with non-linear activation function have mean squared error (MSE) for the training process

IV. Analysis of a Real World Nonlinear-nonstationary Time Series

The plot shows that this is a non stationary-nonlinear time series.

V. Analysis of Oracle Data Using BP Model

Back Propagation Experimental Results:
Oracle Dataset:
Training:
Testing:

![Graph](image1)

![Graph](image2)

![Graph](image3)

![Graph](image4)

Initialize the weight of hidden layer using V matrix, output layer W.

\[ v = [2 \ 1 \ 0; 1 \ 2 \ 0; 3 \ 1; 1 \ 2 \ 0; 3 \ 1] \]

bias of the hidden layer \( vv = [0 \ 0 \ -1] \);

\[ W = [-0.1 \ 0.1 \ 0.1] \]

Bias of the hidden layer \( ww = [-6.5] \);

**V. Analysis of Oracle Data Using ANFIS Model**

**Oracle dataset:**
Oracle data prediction with ANFIS hybrid algorithm using gbell membership function

**Training**

![Graph](image5)

![Graph](image6)

![Graph](image7)

![Graph](image8)
VI. Daily forecasting error and average error based on different methods:

VII. Error Analysis

The details of the error analysis of the real world time series of stock data due to the methods discussed above are explained below. The mean absolute percentage error (MAPE) is used to estimate the performance of the trained prediction for the test input pattern. This method is used to minimize the MAPE for testing input patterns so as to display a better prediction model for forecasting stock price trading.

\[
MAPE = \frac{\sum_{i \leq j \leq N} |e_j|}{N} \times 100
\]

Where \(e\) is the error i.e. difference between actual stock market index and the network output of \(j^{th}\) pattern, \(N\) is the number of input pattern used for testing for validation. The predicted error in case of back propagation is 0.15 and for the same data set in wavelet model is 0.1.

VIII. Conclusion

Forecasting the stock market is of great interest because successful predict of stock price may be guaranteed benefits. The task is very complicated and very difficult for the traders to make decision on buying or selling on instrument. In the study of different models shows that they are able to predict the stock. Among the four algorithms back propagation is suitable for linear input pattern. The effect of wavelet neural network is better than general network for predicting complex financial signals, but we should pay attention to the problem of confusing signal frequency when constructing wavelet neural network. We use Daubechies wavelet function as activation function of hidden layer to construct wavelet neural network, which can provide a reference tool for short-term investment decision of stock market. It is applied to the stock market data set which is a non stationary nonlinear time series.
The results demonstrate the immense capabilities of neuro-fuzzy architecture like ANFIS in implementing complex time series prediction and decision making tasks. It clearly shows its importance in nonlinear system modeling where other conventional methods have not had much success. The short coming of the method developed above includes short-time prediction capabilities, non real time data processing and prediction. The result generated by decision tree for the stock market pattern trend is suitable for short term goals. The experimental results shows that day-a-head prediction is more accurate than monthly and weekly. The above models are suitable for resulting good output, where they can be applicable. Some of them are suitable for short term and long term prediction. It’s the investor’s interest to choose the model as for his/her investment term. These technologies are designed to help investors discover hidden patterns from the historic data that have probable predictive capability in their investment decisions. The method developed above includes short-time prediction capabilities, real time data processing and prediction.

REFERENCES