Integrated Intelligent Research (IIR)
International Journal of Computing Algorithm
Volume 02, Issue 02, December 2013, Page No.138-141
ISSN: 2278-2397

Adoption of Neural Network in Forecasting the Trends of Stock Market

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Abstract - The stock market is a very complicated nonlinear dynamic system, it has both the high income and high risk properties. So the forecast of stock market trend has been always paid attention to by stockholders and invest organization. Forecasting stock prices and their trends are important factors in achieving significant gains in financial markets. In this paper, a neural network-driven fuzzy reasoning system for stock price forecastis proposed on the basis of the trends of stock market.

Keywords: Fuzzy logic, neural network, forecasting stock price,Market Momentum Indicators , Market Volatility Indicators , Market Trend Indicators, Broad Market Indicators, General Momentum Indicators.

I. INTRODUCTION TO FUZZY NEURAL NETWORK

In this section we just recall that the notion of neural network is eminently suited for approximating Fuzzy Controllers and other types of Fuzzy Expert Systems. The following features, or some of them, distinguish Fuzzy Neural Networks from their classical counter parts.

I. Inputs are Fuzzy numbers
II. Outputs are Fuzzy numbers
III. Weights are Fuzzy numbers
IV. Weighted inputs of each neuron are not aggregated by summation. But by some other aggregation operation.

We just recall the definition of Neural Network for the sake of completeness.

Definition 1.1: A neural network is a computational structure that is inspired by observed process in natural network of biological neurons in the brain. It consists of simple computational units, called neurons that are highly interconnected. Each interconnection has a strength that is expressed by a number referred as weight.

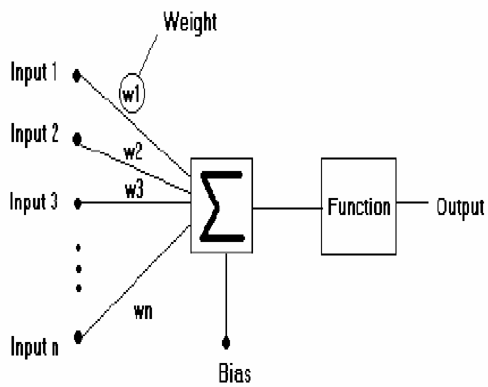
Definition 1.2 The bias defines the value of the weighted sum of inputs around which the output of neuron is most sensitive to changes in the sum. Now we proceed on to define the notion of Neural Network. In Neural Network bias plays an important role. So we take the bias as an input with value – 1 and its corresponding weight is the sum of the average of the other input weights.

The class of sigmoid function S_β, defined by the formula.

$$S_\beta(a) = (1 + \exp\{-\beta a\})^{-1}$$

Then, the output of the neuron is defined by

$$Y = S_\beta\left(\sum_{i=1}^{n} W_i X_i - \theta\right)$$



whereβ is a positive constant (Steepness parameter), θ is called the bias of the neuron, since θ the bias is considered as an input, $x_0 = -1$ and the associated weight $w_0 = \theta$.

Then the output now is given by $Y = S_\beta\left(\sum_{i=0}^{n} W_i X_i\right)$,

where W_i is the weights given by the experts and $S_\beta(a) = (1 + \exp\{-\beta a\})^{-1}$.

1.2. The description and justification

The ability to accurately predict the future is crucial to many decision processes in planning, organizing, scheduling, purchasing, strategy formulation, policy making and supply chains management and so on. Therefore, prediction/forecasting is an area where a lot of research efforts have been invested in the past. Yet, it is still an important and active field of human activity at the present time and will continue to be in the future (Zhang et al., 2004). Stock price prediction has always been a subject of interest for most investors and financial analysts. Nevertheless, finding the best time to buy or sell has remained a very difficult task for investors because there are other numerous factors that may influence stock prices (Pei-Chan and Chen-Hao, 2008; Weckman, 2008). Stock market prediction has remained an important research topic in business and finance. However,stock markets environment are very complicated, dynamic, stochastic and thus difficult to predict (Wei, 2005; Yang and Wu, 2006; Tsanga et al., 2007; Tae, 2007). Financial forecasting is of considerable practical interest. Themost common approaches to stock price prediction arefundamental and technical analysis. The fundamental analysis isbased on financial status and performance of the company. The

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application of ANN to financial forecastinghave been very popular over the last few years (Kate and Gupta,2000; Abu-Mostafa el al., 2001; Defu et al., 2005; Khashei,2009; Mehdi and Mehdi, 2010).In this study artificial neural network with marketindicators were used as the trends to forecast the investor.

Stock market forecasting involves the analysis of several hundred indicators to augment the decision making process. Stock market indicators are mostly proven statistical functions, some of which are very simple in nature. Analysts are required to identify indicators that are useful to them by meticulous screening methods that may be time consuming and may have some undesired financial repercussions. Stock market trading has been considered a risky and volatile business and traders have generally resorted to two broad types of analysis. Use of traditional, proven indicators and the interpretation of patterns and charts. Using the former technique provides mediocre accuracy with a lower risk limit, while the latter provides high accuracy with a higher risk limit. The current research on stock market forecasting involves artificial intelligence techniques and real time computing to utilize the advantages of the above mentioned traditional techniques and provide an accurate forecast with a high confidence limit. One study required high computing power and a substantial amount of time for increasing the accuracy of the model.

Artificial Neural Networks have been used by several researches for developing applications to help make more informed financial decisions. Simple Neural Network models do a reasonably good job of predicting stock market price motion, with buy/sell prediction accuracies considerably higher than traditional models. This performance is being improved by adding more complexity to the network architecture and using more historical data. Different types of network architectures such as Multi LayerPerceptron's, Generalized Feed Forward Networks and Radial Basis Functions are becoming increasingly popular and are being tested for higher accuracy. Many researches are also investigating the possibility of adding additional indicators that may help the Neural Network improve training and performance while testing on production data. Neural Networks show potential for minimizing forecasting errors due to improvements made in training algorithms and increased availability of indicators.
One unique and important property of the Artificial Neural Network is the exceptional structure of the information processing system. It is made of number of highly interconnected processing elements that are very similar to neurons and are joined by weighted connections that are very similar to the synapses.

Artificial Neural Networks have been used since about the late 1950 's. Today a number of complex real world problems are being solved efficiently using the Artificial Neural Networks.

Artificial Neural Networks are efficient pattern recognition engines and strong classifiers with the ability to generalize in making decisions about imprecise input data. They offer excellent solutions to a variety of classification problems. Kunhuang and Yu (2006) used backpropagation neural network with technical indicators, the study findings showed that that ANN has better forecast ability than time series model. Zhu et al., 2007 also used technical indicators with ANN and their findings revealed that ANN can forecast stock index increment and trading volume will lead to modest improvements in stock index performance. Tsanga el al., 2007 used ANN withtechnical indicators to create trading alert system and their findings showed that ANN can effectively guide investors when to buy or sell stocks. Avci (2007) also used ANN to forecastingdaily and sessional returns of the Ise-100 Index and his finding demonstrated that ANN can be used effectively to forecast daily and sessional returns of the Ise-100 Index. Kim and Lee, 2004; Stansel and Eakins, 2004; Chen el al., 2005; Lipinski, 2005; De Leone et al.,2006; Roh, 2007; Giordano et al., 2007; Kyungjoo et al., 2007; Al-Qaheri et al., 2008; Bruce and Gavin, 2009; Mitra, 2009; Mohamed, 2010; Esmaeil et al., 2010; Tiffany and Kun-Huang,2010). Recent research tends to hybridize several artificial intelligence (AI) techniques with technical indicators with the intention to improve the forecasting accuracy, the combination of forecasting approaches has been proposed by many researchers (Rohit and Kumkum, 2008; Khashei el al., 2008).From their studies, they indicated that the integrated forecasting techniques outperformed the individual forecast. However, O'Connor and Maddem (2006) used fundamental indicators with ANN and their findings revealed that ANN has forecast ability in stock market because it has better return than overall stock market. Other research works that engaged the use of fundamental indicators to forecast stock prices (Atiya el al., 1997; Quah and Srinivasan, 1999; Raposo and Crux, 2002).

Hence, it is pertinent to apply a neural network to study the market trend for the confused customers of the stock market. Hence, we adopt the neural network to study the trends of stock market using the indicators of the stock market on the basis of the expert's opinion.

1.3. Adaptation of the Neural Network to the Problem
Here we describe the problem together with the assumed notations and construct the neural network based on the experts opinion on a few factors like.

X_0	-	Market Momentum Indicators
X_1	-	Market Volatility Indicators
X_2	-	Market Trend Indicators
X_3	-	Broad Market Indicators
X_4	-	General Momentum Indicators

Each input $X_0, X_1, \ldots, X_4$ are associated with real numbers called the weights, namely $W_0, W_1, \ldots, W_4$ whose value lie in the interval [0,1].

X_0 - Market Momentum Indicators
Using a proprietary formula, a ratio of the percentage of designated stocks currently trading above their respective 50-day moving averages is computed. This number is reported daily as the "ratio" and is the basis for all other calculations. Two moving averages of that ratio are also calculated and reported, a 10-day and a 25-day. The movement and behavior of these two moving averages defines the value of the Momentum Indicator for determining the general market trend. In its simplest and most basic interpretation, an uptrend is

signaled when the 10-day moving average crosses above the 25-day moving average and the 25-day moving average turns up. Conversely, a downtrend is signaled when the 10-day moving average crosses below the 25-day moving average and the 25-day moving average turns down. The Momentum Indicator is prone to signaling many turns, especially when the underlying stock market is confined to a narrow trading range.

X_1 - Market Volatility Indicators

Market Volatility Indicatorsdescribes volatility as "the rate and magnitude of changes in price." In simple English, volatility is how fast prices move. When the market is calm and moving in a trading range or even has a mild upside bias, volatility is typically low. On these kinds of days, call option buying (a bet that the market will move higher) generally outnumbers put option buying (a bet that the market will go down). This kind of market typically reflects complacency, or a lack of fear. Conversely, when the market sells off strongly, anxiety among investors tends to rise. Traders rush to buy puts, which in turn pushes the price of these options higher. This increased amount investors are willing to pay for put options shows up in higher readings on the Market Volatility Indicators. High readings typically represent a fearful marketplace. Paradoxically, an oversold market that is filled with fear is apt to turn and head higher.

X_2 -Market Trend Indicators

A series of technical indicators used by traders to predict the direction of the major financial indexes. Most market indicators are created by analyzing the number of companies that have reached new highs relative to the number that created new lows, also known as market breadth.Some of the most common market indicators are: Advance/Decline Index, Absolute Breadth Index, Arms Index and McClellan Oscillator. A general outlook on the market's direction is useful for traders looking for strength in individual equities because they ensure that the broader market forces are working in their favor.

X_3 - Broad Market Indicators

All of the technical analysis tools discussed up to this point were calculated using a security's price (e.g., high, low, close, volume, etc). Before buying and selling shares, it is necessary to assess2 market indicator. The industry group to which the share is associated. The Stock Exchange supplies index figures on different groups. A market indicator signals 'the state of the economy for the coming months. When market indicators show a drop in the price level over a brief time period, moving down excessively and quickly, the market becomes "oversold". To handle broad market indicators in the most efficient way, use them for trading against broad market indices through futures, mutual funds and options. In general, broad market indicators can be used for trading against broad market indices through forex, options, futures, and mutual funds.

X_4 – General Momentum Indicators

The momentum indicator at core of the oscillator family, and understanding how to interpret this indicator will help to better understand all the other oscillators. Momentum measures the rate of change rather than price itself. A fundamental principle in using momentum as an indicator is to buy when momentum crosses zero (or 50 in the case of RSI) to the upside, or to sell when it crosses below zero to the downside. Another basic principle of interpreting momentum is *divergence* – this occurs when price is rising or falling and momentum starts to flatten or move in the opposite direction. Momentum measures the velocity of price changes – the acceleration rate of ascent or descent of price. Momentum is a leading indicator in that it turns before price itself does. A 10 day momentum is a commonly used time period, however any time period can be used. The longer the time period used the smoother the line appears. The Momentum is measured using price changes over a fixed time period.

We have obtained 5 experts opinion, the corresponding weight

	W_0	W_1	W_2	W_3	W_4
Expert 1	0.73	0.69	0.50	0.87	0.70
Expert 2	0.80	0.67	0.48	0.72	0.43
Expert 3	0.63	0.80	0.53	0.73	0.60
Expert 4	0.78	0.75	0.81	0.72	0.52
Expert 5	0.75	0.47	0.62	0.72	0.68

The average of the weights are given by the experts namely E_0, E_1, …, E_4.

E_0	E_1	E_2	E_3	E_4
0.69	0.58	0.67	0.70	0.62

By taking the input as the average of the weights given by the experts and the value of bias is kept as in the case of neural network to be –1. In general, using this Neural Network, we can extend to 5 number of experts say E_0, E_1, … , E_4 and their corresponding output is given by,

$$Y_i = S_\beta \left(\sum_{i=0}^{5} W_i X_i \right),$$

X_0	X_1	X_2	X_3	X_4
-1	0.68	0.59	0.75	0.59

where W_i is the weights given by the experts and $S_\beta(a) = (1 + \exp\{-\beta a\})^{-1}$. So we get output from the following table

Y_0	Y_1	Y_2	Y_3	Y_4
0.75	0.68	0.76	0.74	0.71

From the output, we see that the overall opinion of the experts regarding the trends of stock market to be > 0.5. All factors contribute equally responsible for trends of stock market but out of which Y_2 stands maximum that is the Market Trend Indicators created by the stock market the other problems. The problems are given order Y_0,Y_3,$Y_4$and Y_1.

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