ACCURACY DRIVEN ARTIFICIAL NEURAL NETWORKS IN STOCK MARKET PREDICTION

Selvan Simon[1] and Arun Raoot[2]

[1]Asst. Professor, P. G. Dept. of Computer Sci., SNDT Women's University, Mumbai
selvansimon@gmail.com
[2] Professor, National Institute of Industrial Engineering, Vihar Lake, Mumbai
adraoot@gmail.com

ABSTRACT

Globalization has made the stock market prediction (SMP) accuracy more challenging and rewarding for the researchers and other participants in the stock market. Local and global economic situations along with the company's financial strength and prospects have to be taken into account to improve the prediction accuracy. Artificial Neural Networks (ANN) has been identified to be one of the dominant data mining techniques in stock market prediction area. In this paper, we survey different ANN models that have been experimented in SMP with the special enhancement techniques used with them to improve the accuracy. Also, we explore the possible research strategies in this accuracy driven ANN models.

KEYWORDS

Artificial Neural Networks, Multilayer Perceptron, Back Propagation, Stock market prediction & Prediction accuracy.

1. INTRODUCTION

Investors in stock market want to maximize their returns by buying or selling their investments at an appropriate time. Since stock market data are highly time-variant and are normally in a nonlinear pattern, predicting the future price of a stock is highly challenging. With the increase of economic globalization and evaluation of information technology, analyzing stock market data for predicting the future of the stock has become increasingly challenging, important and rewarding. With the development of ANN, researchers are hoping to demystify the stock market because of its great capability in pattern recognition and machine learning problems such as classification and prediction.

This paper surveys the ANN models used in SMP. It is organized as follows: section 2 introduces the ANN. Section 3 introduces the stock market fundamentals and describes common models used in the stock market prediction. Section 4 explores ANN models, their variations, and special techniques applied in SMP. Finally, in section 5, we discuss a number of strategies for improving the prediction accuracy.

DOI: 10.5121/ijsc.2012.3203

2. ARTIFICIAL NEURAL NETWORKS

Nowadays, ANN is considered as a common data mining method in different fields like finance, economy, medical, business, industry, science, and so on. ANNs are computer models built to emulate the human pattern recognition function.

2.1. Structure of an ANN

It consists of fundamental processing elements called neurons. These neurons are distributed in few hierarchical layers. Most of the neural networks are three layered: input, middle or hidden, and output. Generally, there occurs no data processing at the input layer. The input layer takes the inputs and passes to the middle layer. There can be more than one middle layers. These hidden layers are where all the complexity resides and the computations are done. The data or information is distributed through the network and stored in the form of interconnections. These interconnections between artificial neurons are called weights. Fig.1 shows a representation of an ANN and a simplified neuron. A neuron, like other linear or polynomial approximation, relates a set of input variables {Xi}, i=1,……,n to set of one or more output variables {Yj}, j=1,…,m. But, in case of ANN, the input variables are mapped to the output set by squashing or transforming by a special function f, known as activation function. Each neuron also has a bias assigned to it. Each neuron receives an input signal, which transmits through a connection that multiplies its strength by the scalar weight w. A bias is added to the weighted input and is then passed through the activation function to get the desired output [1].

2.2. Characteristics of ANN

The weight w and the bias b are adjustable parameters of the neuron. The weights between two neurons in two adjacent layers are adjusted to reduce errors through an iterative training process while training samples are presented to the network. This training process lasts till the error between actual output and expected value meets the requirements, so that the satisfactory weights and threshold can be achieved. Thus, they learn the relationship inherent in variables from a set of training sample. Back propagation (BP) algorithm is the most widely used training algorithm for ANN. They store the captured knowledge and make it available for future use. ANN has the capability to adapt the network parameters to the changes in the studied system. Moreover, when the system under study is non-stationary and dynamic in nature, the ANN changes its network parameters in real time [1].

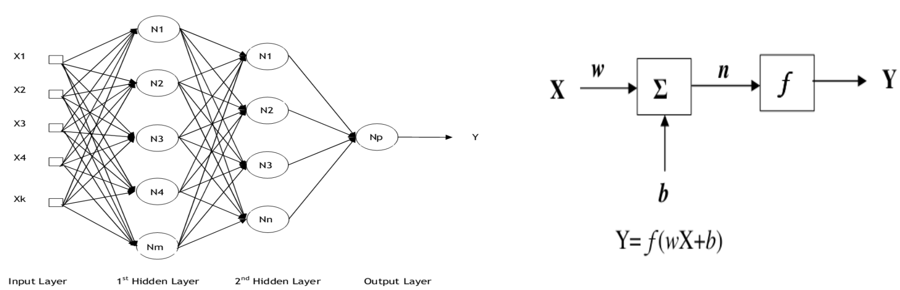

Fig. 1 Representation of an ANN and a simplified neuron

3. APPLICATIONS OF ANN IN STOCK MARKET

In this section, we briefly introduce the stock market and the evolution of the stock market prediction models.

3.1. Stock market basics

A stock market is a public market for the trading of company stock and derivatives at an agreed price. Stock market gets investors together to buy and sell shares in companies. Share market sets prices according to supply and demand. Hence, a stock that is highly in demand will increase in price, whereas a stock that is being heavily sold will decrease in price. Primary market deals with the new issues of securities directly from the company. An official prospectus is published under the corporation law that contains all the information about the company that is reasonably required by the investors to make an informed investment decisions. The existing securities are bought and sold in the secondary market among traders. A share is a document issued by a company, which entitles its holder to be one of the owners of the company. By owning a share one can earn a portion of the company's profit called dividend. Also, by selling the shares one gets the capital gain. However, there is a risk of making a capital loss, if selling price of the share is lower than the buying price. Stock is a collection or a group of shares. Stock Exchanges act as the clearing house for each transaction, that is, they collect and deliver the shares, and guarantee payment to the seller of a security. The smooth functioning of all these activities facilitates business expansion, economic growth, employments and promotes production of goods and services. To be able to trade a security on a certain stock exchange, it has to be listed there. Listing requirements are the set of conditions imposed by a given stock exchange on companies that want to be listed. Stock brokers are licensed agents to trade shares. They have direct access to the share market to do share transactions. They charge a fee for this service. Traders buy and sell financial instruments such as stocks, bonds and derivatives. Traders are either professionals working in a financial institution or a corporation, or individual investors [2].

3.2. SMP using traditional models

The characteristic that all stock markets instruments have in common is the uncertainty related to their future states. This feature is undesirable for the investors, but unavoidable when stock market is chosen for investment. While numerous attempts have been made, no method has been discovered so far to accurately predict the stock price. However, stock analysts have been using various approaches for predicting stock market. In this section, we briefly explain the important approaches used in the stock market prediction.

3.2.1. Technical Analysis

Technical analysis is based on mining rules and patterns from the past prices of stocks. It analyses the financial time series data to forecast stock market using indicators of technical analysis. Technical analysts utilize charts and modelling techniques to identify trends in price and volume. But charts or numeric data contain only the events and not the cause why it happened. It is believed that market timing is critical and opportunity can be found through the careful averaging of historical price and volume movements and comparing them against current price [3].

3.2.2. Fundamental Analysis

Fundamental analysis investigates the factors that affect supply and demand. The goal is to gather and interpret this information and act before the information is incorporated in stock price.

Fundamental analysis is based on economic data of companies that they have to publish regularly, for example, annual and quarterly reports, auditor's reports, balance sheet, income statements, etc. This method is concerned more with the company rather than the actual stock. The analysts make their decisions based on the past performance of the company, its earnings forecast, the particular industry sector and the overall economy [3].

3.3. SMP using ANN

ANN is nonlinear in nature and since the stock market returns change in a nonlinear pattern, the ANN is more appropriate to model these changes [4]. Indeed, ANN is significantly more accurate than its traditional competitive model, multiple linear regression analysis for SMP [5]. Moreover, predicting stock index with traditional time series analysis has proven to be difficult. Because of its easy adaptation to noisy data and ability to extract useful information from large data set and to solve complex non-linear problems, ANN suits in predicting stock returns [6].

4. Competitive ANN Models In SMP

While attempting to improve the SMP accuracy, researchers have experimented with many variations of ANN models. Here, we discuss these ANN models and techniques:

4.1. Improving ANN accuracy by relevant ANN model

By comparing various ANN models and one can choose the model and its learning algorithm most suitable for the given application, prediction target and problem situation to get the best result:

Saad et al. [7] compared three networks for stock trend predictions. Authors compared the time delay neural networks (TDNN), recurrent neural networks (RNN), and probabilistic neural networks (PNN) neural networks, utilizing conjugate gradient and extended Kalman filter training for TDNN and RNN. The history of the daily closing price was analysed. The three networks showed comparable results. TDNN was moderate with respect to implementation complexity and memory requirement. PNN was more suitable for stocks which do not need training on long history, like Apple stock. RNN had the capability to dynamically incorporate past experience.
Quah [8] presented methodologies to select equities based on soft-computing models which focus on applying fundamental analysis for equities screening. The performance of three models was compared: multilayer perceptron (MLP), adaptive neuro-fuzzy inference systems (ANFIS) and general growing and pruning radial basis function (GGAP-RBF). The author applied several benchmark matrices to compare performance. The author also suggested how equities can be picked systematically by using relative operating characteristics (ROC) curve. ROC curve has two variables from confusion matrix, which are True Positive (TP) rate and True Negative (TN) rate. One can maximize TP and minimize TN for optimal performance. The average appreciation of equities was almost doubled for all three soft-computing models than the average market appreciation.

Charkha [9] used the feed forward back propagation neural networks (BPNN) with early stopping and radial basis networks (RBN) to predict the trend of stock price (i.e. classification) and to predict the stock price (i.e. value prediction). Fundamental or technical indicators were not used in this research as basic objective of this research was to determine the usability of ANN in predicting the future prices based on past prices alone. It was observed that BPNN was better for trend prediction and RBN was better for the value prediction.

Naeini et al. [10] used two kinds of neural networks, a feed forward MLP and an Elman recurrent network to predict a company's stock value based on its stock share value history. The experimental results showed that the application of MLP neural networks was more promising in predicting stock value rather than Elman recurrent networks and linear regression method. However, based on the standard measures it was found that the Elman recurrent network and linear regression can predict the direction of the changes of the stock value better than the MLP.

4.2. Improving ANN accuracy by statistical techniques

By integrating various standard statistical multivariate analytical techniques with ANN models, one can improve the prediction accuracy:

Wang and Leu [11] used recurrent neural networks (RNN) with BP for forecasting mid-term price trend of Taiwan stock market. The network was trained using features extracted from Auto Regressive Integrated Moving Average (ARIMA) analyses. An ARIMA model is a linear non-stationary model that uses difference operator to convert non-stationary series to stationary. It does not work well in modelling non-linear series by itself. The experimental results showed that the ARIMA-based recurrent neural network was capable of predicting the market trend with acceptable accuracy.

Thenmozhi [12] applied neural networks to predict the daily returns of the Bombay stock exchange (BSE) Sensex. An MLP using back propagation network was used. It was found that the predictive power of the network model was influenced by the previous day. The study showed that satisfactory results could be achieved by applying MLP to predict the BSE Sensex. A sensitivity analysis was done in order to determine the relative importance of each input on the output, once the network was fully trained. Sensitivities were determined by cycling each input for all training patterns and computing the effect on the MLP output response. It indicated that the immediate previous day return contributed significantly in predicting the returns compared to the first three-day returns used for prediction.

Al-Luhaib et al. [13] examined Saudi stock market (SSM) to predict the direction of daily price changes. BPNN was applied to predict the direction of price changes for the stocks listed in SSM. The target had a representation of three classes 1, -1 and 0 that respectively represent the increase, decrease or insignificant change in the stock prices. The use of dynamic target was a novel enhancement to the traditional objective function. The weights updates through different training epochs were slowly changed to smooth the convergence and achieve the generalization by reaching the ideal target. The classification result was improved by using dynamic target.

Zhao et al. [14] predicted the stock price using BPNN by considering a single closing price as the time series vector. The authors made a two steps forecast approach. First, use Gray correlation analysis to choose the set of variable which can describe the characteristics of the state of the stock market from a number of technical indicators. Then classify the state of stock market by the self-organizing feature map (SOFM) network. And based on this classification, BPNN was used for prediction. The results showed that the predictive accuracy of SOFM-BP model was better than that of the traditional BPNN model.

ANN models were widely applied for stock market prediction. However, the parameter settings of the networks are normally determined through a trial-and-error methodology. Hsieh et al. [15] integrated the design of experiment (DOE), Taguchi method, and BPNN to construct a robust engine to improve the prediction accuracy. Adopting data from Taiwan Stock Exchange (TWSE), the technical analytical indexes of the listed stocks of TWSE were computed. The research results indicated that the DOE-based predictor could effectively improve the forecasting rate of stock price variations.

4.3. Improving ANN accuracy by special algorithms

It is also possible to combine special algorithms with ANN for denoising, selecting and optimizing parameters to improve accuracy of ANN models in SMP:

Lee and Lim [16] presented a methodology for forecasting the daily Korea composites to price index (KOSPI) using neural networks with self-adaptive weighted fuzzy membership functions to improve forecasting accuracy. The degree of classification intensity was obtained by bounded sum of weighted fuzzy membership functions extracted by this network. The Haar wavelet function was used as a mother wavelet. A set of five extracted coefficient features of the Haar wavelet transform were presented to forecast KOSPI. This model demonstrated an excellent capability in SMP.

Li and Liu [17] analysed the complexity of the stock price system and used BPNN for stock market prediction. They presented a method for determining the number of hidden layers, selection and pre-treatment of sample data and determination of preliminary parameters. To avoid local extreme and promote convergence speed, the network trained by the Levenberg-Marquardt BP algorithm, based on numerical optimization. Simulation experiments on Shanghai stock exchange index indicated that this algorithm could make efficient short-term prediction.

Olatunji et al. [18] used ANN model for the predicting stock market. The model was based on SSM historical data covering a large span of time. They used only the closing price of the stock as input to the system. The number of windows gap to determine the number of previous data to be used was based on an algorithm for searching optimal parameter. The optimized parameter was then used to build the final ANN model. The experimental results indicated that the proposed ANN model predicted the next day closing price stock market value adequately accurate.

It is evident that the dominant data mining technique used in SMP are ANN models [19], [20]. Also, MLP with BP training found to be the most widely used ANN model in SMP. Researchers have combined various statistical, mathematical and special algorithms with ANN models to improve prediction accuracy. We have summarized these enhancement techniques in Table 1.

Table 1. Enhancement techniques for improving accuracy in SMP

Sr.	Researchers	Year	Enhancement Techniques used with ANN models
1	Wang and Leu	1996	ARIMA to convert non-stationary series to stationary
2	Saad et al.	1998	Choosing problem specific ANN model
3	Thenmozhi	2006	Sensitivity analysis to find importance of each input
4	Al-Luhaib et al.	2007	Dynamic target to smooth the convergence
5	Lee and Lim	2007	Self-adaptive weighted fuzzy membership functions
6	Charkha	2008	Choosing target specific ANN model
7	Quah	2008	ROC curve to select equities
8	Li and Liu	2009	Levenberg-Marquardt algorithm to avoid local extreme
9	Zhao et al.	2009	Gray correlation analysis to choose the set of variable
10	Naeini et al.	2010	Choosing target specific ANN model
11	Hsieh et al.	2011	Taguchi method for parameter optimization
12	Olatunji et al.	2011	Heuristic algorithm for parameter optimization

5. STRATEGIES FOR IMPROVING ACCURACY

Despite the extensive research on applying ANN to SMP, this field is still evolving to improve the accuracy. We have isolated some of the challenges and research strategies in this area:

5.1. Hybrid analysis

When applying machine learning and data mining to stock market data, researchers have mainly focused in technical analysis to see if our algorithm can accurately learn the underlying patterns in the stock time series. ANN can also play a major role in evaluating and predicting the performance of the company and other similar parameters helpful in fundamental analysis. Neither all possible technical information nor all available fundamental information or combinations of both have been tested. Thus, both ideas have to be regarded [21]. The most successful ANN stock prediction models may use some sort of a hybrid analysis model involving both fundamental and technical indicators [3]. Building an ANN model that combines the process of the technical and fundamental analyses will improve the prediction results.

5.2. Choice of inputs

The future returns of a stock can be based on a number of factors such as earnings per share, capital investment, daily transaction volume, market share, stock prices, leading indicators, macroeconomic data, interest rates, inflation rates, political issues, and many others. [11], [22–25]. Different stock market parameter are also used: movement of index, major stock market indices, domestic minimum loan rate, gold price [26], results of fundamental analysis [8], moving average crossover inputs based on technical analysis rules [27] and so on. Further research is anticipated to incorporate additional inputs that influence stock returns with this neural approach [28]. Identifying, categorizing, and sorting the parameters in the order of their influence on stock price using multivariate techniques will provide the most useful input collection.

5.3. Training ANN with stock market data

The usage and training of an ANN is an art [29]. Pre and post data processing issues such as selecting, sampling, cleaning, filtering, denoising, normalizing, deseasonalising, validating, pruning, segmenting, organizing, identifying, optimizing data for training ANN, for stock market data are important. While applying an ANN model in SMP, care should be taken at every single process. Developing methodologies for processing stock market data will improve the accuracy.

5.4. Lagged data input

In multi lag prediction, some predicted values are also used to predict futures values. The extent of this lagged data to be incorporated and weights allotted to them are design issues. To predict the five-day future index value for the market, Walczak [30] used the set of one-day, two-days, and five-days lags of the closing value, along with the corresponding one-day, two-days, and five-days normalized average trading volumes for the respective index markets as the input values for ANN. An alternative input is to use lagged differenced time-series data [11]. One can consider the lagged data up to a number of weeks plus the current week and use numerical methods like forward and backward difference, interpolation to prepare input using the past, current and recently predicted data along with their errors with appropriate weights.

5.5. ANN components optimization

MLP with BP training has been the most commonly used ANN model in SMP. The selection of appropriate number of hidden layers, number of neurons in each layer, size of the training set, initial values for weights, inputs to be included, activation function are the key design issues of this model. Tweaking these components iteratively and applying tools like DOE, one can arrive at the combination of the components that yields the best prediction.

5.6. Targets in stock market

ANN models should be considered along with the target application. For example, stock market trend prediction and stock market prediction may require different ANN models and data. Targets in stock market may be predicting market indices, market trend, market volatility, buy-hold-sell alarm, high-low risk-return classification, triaging best to worst stock for trading strategy and so on. The forecasting may be for long term, short term, given period, or instant. It may be for a stock or a sector. Identifying the most suitable ANN model and data for a specific prediction target will enhance the accuracy.

5.7. Hybrid models

One can divide the complex stock market prediction tasks into simpler subtasks, perform the task and integrate the results to get better performance. Every data mining models has its own strengths and weaknesses. By applying more than one data mining techniques, say genetic algorithm and neural networks on two different subtasks, we can take the advantages of their strengths to subsume their weaknesses [4]. Hybridization using two-layer and three-layer approach have attracted many data mining researchers.

6. CONCLUSION AND FUTURE WORKS

ANN plays an important role in SMP. ANN models have outperformed other traditional models. Also, MLP with BP training found to be the most widely used ANN models in SMP. There are variations in ANN model. It is important to choose the appropriate ANN model considering the problem target. Various statistical techniques may be used to pre-process the data for improving performance. Also, special algorithms may be combined with ANN to improve accuracy. There are several challenges and research scopes for improving the prediction accuracy. We will be working on the strategies in section V, in future.

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Authors

Selvan Simon is an Assistant Professor in the Post Graduate Department of Computer Science, S N D T Women’s University, Juhu, Mumbai. His area of interest is Stock Market Intelligent Systems, Decision Sciences, Web Technologies, E-Trading and M-Trading . Email: selvansimon@gmail.com

Arun Raoot is a Professor in the Department of Industrial Engineering and IT Applications, National Institute of Industrial Engineering, Vihar Lake, Mumbai. His research interest includes Industrial Engineering, Facilities Planning, and IT Applications. Email: adraoot@gmail.com