REVIEWS

Role of soft computing techniques in predicting stock market direction

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Abstract

The stock market is a complex and dynamic system with noisy, non-stationary and chaotic data series. Prediction of a financial market is more challenging due to chaos and uncertainty of the system. Soft computing techniques are progressively gaining presence in the financial world. Compared to traditional techniques to predict the market direction, soft computing is gaining the advantage of accuracy and speed. However the input data selection is the major issue in soft computing. The aim of this paper is to explain the potential day by day research contribution of soft computing to solve complex problem such as stock market direction prediction. This study paper synthesizes five reference papers and explains how soft computing is gaining the popularity in the field of financial market. The selection of papers are based on various models wich are processing different input parameters for predicting the direction of stock market.

Key words

Financial market, Prediction, Soft computing, Technical indicator

1 Introduction

Stock market direction prediction has always been subject of interest for most investors and professional analysts. The soft computing field covers a set of techniques that try to mimic the ability of the human mind to effectively employ modes of reasoning that are approximate rather than exact. The term was coined by Zadeh in the early nineties and its foundations can be traced back to earlier works such as paper on fuzzy sets [1] paper on complex systems and decision processes [2]; or his paper on possibility theory and soft data analysis. The concept was the subject of a specific paper published in 1994 [3]. Zadeh suggests that the main constituents of soft computing are fuzzy logic, neural network theory and probabilistic reasoning.

The difference between traditional computing, also known as hard computing, and soft computing, is based on the importance given to issues like precision, certainty and rigor. These elements are at the core of hard computing. The aim of this paper is to explain the contribution of soft computing to solve complex problem such as stock market direction prediction.

This paper is structured as follows: the second section deals with major work done on each of five research papers [4-8]. The third section draws commonalities and differences between these papers to establish the technical gap. Finally, present conclusions.

2 Reference papers description

2.1 Soft computing techniques applied to finance

This paper presents soft computing relevant application areas, and to serve as an introduction to soft computing. The research paper explains the application of soft computing in financial cases where we deal with problems whose nature is highly unstructured or which involve incomplete information or corrupted data, among others. This paper takes the following four cases [4] where the soft computing is playing major role:

- Securities market and foreign exchange prediction: The aim here is to obtain accurate predictions for the behavior of a reference index soft computing would generally take over the role of ARMA or GARCH econometric modeling.
- Trading: The aim of these would be exploiting regularities in price formation mechanisms in order to gain returns over a specific benchmark strategy, often buy-and-hold.
- Automated credit scoring: They are generally classification systems that recommend either accepting or rejecting an application based on many different approaches [9] that differ in accuracy and capability to extract meaningful decision rules.
- Business failure prediction: One of the most important research lines approaches this as a classification task where the companies are classified in different categories depending on their financial soundness according to a set of relevant parameters.

The conclusion drawn from this paper is in contrast to hard computing, soft computing methods deal effectively with the ill-structured problems that we find in the real world. Fuzzy logic, neural networks and probabilistic methods make a solid set that, either in their pure form or combined in hybrid solutions, can be used to tackle issues related to imprecision, learning and uncertainty.

2.2 Surveying stock market forecasting techniques Part II: Soft computing methods

This paper is basically research study paper for various soft computing techniques applied to solve financial market various complex problem. This paper surveys more than 100 related published articles that focus on neural and neuro-fuzzy techniques derived and applied to forecast stock markets. Classifications are made in terms of input data, forecasting methodology, and performance evaluation and performance measures used. Through the surveyed papers, it is shown that soft computing techniques are widely accepted to studying and evaluating stock market behavior.

This paper provides review, classifies derived and applied soft computing techniques to stock market problems; the results are presented in terms of five summary tables. The first table lists the respective stock markets authors have modeled. The second table lists input variables (independent variables) to the stock market model. The third table summarizes specific methodologies and model parameters used in each paper to forecast stock markets. The fourth table demonstrates modeling benchmarks of each author's specific approach, as well as any comparisons/discussions made against other techniques; such techniques include artificial neural networks (ANNs), linear and multi-linear regression (LR, MLR), ARMA and ARIMA models, genetic algorithms (GAs), random walk (RW), buy and hold (B & H) strategy, and/or other models. The last table summarizes performance measures used to evaluate each surveyed model.

2.3 A generalized model for financial time series representation and prediction

This paper deals with a model to find the trend reversal using local minimal/maximal by finding various technical pattern and initiated trade. Basically it predicts the trend whether asset security move up, down or range bound. In this paper using various technical patterns first predict the trend. Paper also smoothens the data to minimize the noise. The Critical Point Model (CPM) [6] is the heart of this research. This model is based on local minimal/maximal point which exists in periodically stock market time series. The model can integrate multiple stock analysis techniques into one simple frame works, called CPM. Using soft computing techniques patterns are predicted in this paper.

To verify the utility of the CPM model, develop a system combining the data smoothing, the technical indicators recognition, and the trend reversal prediction under the CPM model. After the data smoothing, the system retrieves turning points from the price data in terms of the trading precision by the previous algorithm. For every turning point, CPM recognizes the trend reversal signals indicated by 30 technical indicators [6]. These turning points and their technical indicators will be considered as the training examples to learn the parameters of a probabilistic model derived from the Markov Network. Probabilistic model is learned by optimizing the Conditional Log Likelihood (CLL) The model can integrate multiple stock analysis techniques into one simple framework. Profit can be made by selling at higher and buying at lower. When model find the uptrend is reversal, one can sell the security, if down trend is reversal then profit can made by buying the security.

2.4 Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul stock exchange

This study attempted to predict the direction of stock price movement in the Istanbul Stock Exchange. Two prediction models were constructed, first one is Artificial Neural Network (ANN) and second one is based on Support Vector Machine (SVM), and their performances were compared on the daily data from 1997 to 2007 [7]. Technical indicators were selected as inputs of the proposed models. This paper experimental results showed that average performance of ANN were better than SVM.

In this paper, a there layered feed-forward (FF) ANN model was structured to predict stock price index movement. Inputs for network were ten technical indicators which were represented by ten neurons in the input layer. The output layer of the network consisted of only one neuron that represents the direction of movement. Back-propagation learning algorithm [10] was used to train the three- layered feed-forward ANN structure in this study. The gradient-descent method was used as the weight update algorithm to minimize RMS%. A tangent sigmoid transfer function was selected on the hidden layer. On the other hand, a logistic sigmoid transfer function was used on the output layer. That is, the outputs of the model will vary between 0 and 1. If the output value is smaller than 0.5, then the corresponding case is classified as a decreasing direction; otherwise, it is classified as an increasing direction in movement.

A support vector machine (SVM) is a family of algorithms that have been implemented in classification, recognition, regression and time series. SVM originated as an implementation of Vapnik's (1995) Structural Risk Minimization (SRM) principle to develop binary classifications. The main idea of support vector machine is to construct a hyper plane as the decision surface such that the margin of separation between positive and negative examples is maximized [11]. For a training set of samples, with input vectors x_i^2 Rd and corresponding labels y_i^2 {+1, -1}, SVM learns how to classify objects into two classes.

2.5 A novel recurrent neural network-based prediction system for option trading and hedging

This paper proposes a novel non parametric method using an ad-hoc recurrent neural network (RNN) for estimating the future prices of war commodities such as gold and crude oil as well as currencies. The proposed network predicts the price accurately and computationally efficient and used in a hedging system to avoid unnecessary risks. This study overcomes the limitations of traditional models whose parameters are calibrated to match only certain conditions. This study state the advantage of non-parametric pricing methods that they rely on the available data to detect patterns within and relationships between inputs to determine asset dynamics as well as pricing processes. The proposed option pricing system is employed in practice within a hedging system to minimize exposed risk.

The Elman Network [12] and Hopfield network [9] are two most popular RNN among various other RNN. C. Quek designed Model network uses values of past data in addition to the previously computed hidden layer outputs, thus creating a form of memory in addition to the information stored in the weight values, which is the pricing dynamics model of the under-lying asset. The proposed network attempts to combine the features of feed-forward and feedback networks with a new error back propagation algorithm to provide a better learning capability. All connections have weights, the values of which are modified during training, stored in weight matrices that constitute the memory of the network. The recurrent connections or feedback from the input layer can be considered as a parallel input layer; these are the hall-marks of a recurrent neural network. The inputs to the network consist of two sets of data. The first set is the data provided by the user and consists of n consecutive values (as determined by MCES) of the features selected in the first stage. The second set consists of the feedback inputs i.e., the delayed hidden layer outputs. The period of trading is determined such that the data is representative of the possible market trends. The optimal training data period is decided by determining the point midway between under-fitting and over- fitting the data. With an extensive set of predictions, the direction of change for the next day has been predicted with about 90% accuracy.

3 Commonalities and differences

Stock market and commodity market provide investor to invest their money. All research study [4-8] described in section II are deals with complex problem where raw data have highly noise due to buying and selling security with different time and different volume. All research study discussed in this paper is used soft computing techniques to solve two different market, stock market and commodity market. These research study [4-7] take the problem example of stock market while research study [8] takes the problem example of commodities and oil. Research study [8] may not provide accuracy on the stock market without modifying its input parameter due to both the stock market and commodity input parameter are affected different way. Even stock market and commodity market may influence each other in some extent. The stock market is highly affected by specific sectors, while commodity market is highly affected by nature changes, consumption etc. Also it will only predict the option price but not derive any conclusion how it will affect the price movement of entire market. The testing case is very limited to commodities such as gold and oil.

The CPM [6] may apply for stock market as well as commodity market due to both markets represents price time series. Research studies [4-7] take input parameter such as security open price, close price, high price, low price, previous closing price, derived price (combination of open, high, close, low) etc., but they are not take any input from derivative market where now a days liquidity and volume is very high. So that the model represented in study [4-7] are not fully represent the whole market input parameter. Even input parameter table represented in research study [8] where other research models represented also miss the derivative segment knowledge representation in input parameter consideration is not available. The performance and prediction accuracy of soft computing techniques are highly relies on selection on input parameter. If some commodity don’t have derivative segment then this model will not work [8].

The prediction methodology in research study [8] has developed CPM model. In this study to reorganization computation cost is very high compare to Kara, Quek [7, 8]. Research study [7] ANN is better predict power compare to SVM, ANN used learning algorithm as back propagation which have the drawback that some time finding the global minima it reach to local minima.

Indeed the last fifteen years have seen a growing awareness and corresponding rise in the activities of derivative securities. Larger part of the money in stock market is flowing into derivative segment. The volume and liquidity are high compare to spot market. So one can extract the knowledge from derivative segment using various derivative parameter such as open interest, change in open interest, Put-Call Ration etc. The research paper [5-7] are not consider derivative segment so they are miss very important knowledge. The research paper [8] considers the derivative segment at some extent and rather than predict the spot price, give important to predict the derivative options.

4 Conclusion

This paper elect the five different research paper and explain systematically how the soft computing techniques predict the financial market using different model. Here we have study historical development of soft computing techniques for solving financial problem [5], the pattern recognize model CPM [6], two most popular NN [7] and corporately prediction accuracy. The study [8] gives great research opportunities to selection of input parameter from fast growing and highly knowledge representation derivative segment.

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