Market Forecasting and Trading Rules Based on Soft Computing Technologies

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Abstract.

Hybrids of the soft computing (SC) technologies have been applied to market forecasting and trading rules, and in many cases have demonstrated better performance than competing approaches. The purpose of this research is to investigate a representative group of these applications and to document the manner in which hybrids of the SC technologies were implemented.

Keywords: soft computing, market forecasting, trading rules, neural networks, fuzzy logic, genetic algorithms

Introduction

Apparently, White (1988) was the first to use neural networks (NNs) for market forecasting. He was curious as to whether NNs could be used to extract nonlinear regularities from economic time series, and thereby decode previously undetected regularities in asset price movements, such as fluctuations of common stock prices. The purpose of his paper was to illustrate how the search for such regularities using a feed-forward NN (FFNN) might proceed, using the case of IBM daily common stock returns as an example. White found that his training results were over-optimistic, being the result of over-fitting or of learning evanescent features. He concluded, "the present neural network is not a money machine."

Since then, it has been well established that fusing the soft computing (SC) technologies of NNs, fuzzy logic (FL) and genetic algorithms (GAs) may significantly improve an analysis (Jain and Martin 1999, Abraham and Nath 2001).[1] There are two main reasons for this. First, these technologies are for the most part complementary and synergistic. That they are complementary follows from the observations that NNs are used for learning and curve fitting, FL is used to deal with imprecision and uncertainty,[2] and GAs are used for search and optimization. Second, as Zadeh (1992) pointed out,

[1] While NNs, FL and GAs are only a subset of the soft computing technologies, they are regarded as the three principal components (Shukla 2000 p. 406).

[2] Following Zadeh (1994 p. 192), in this article the term fuzzy logic is used in the broad sense where it is essentially synonymous with fuzzy set theory.

merging these technologies allows for the exploitation of a tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, and low solution cost.

Market forecasting and trading rules have numerous facets with potential applications for hybrids of the SC technologies. Given this potential and the impetus on SC during the last decade, it is not surprising that a number of SC studies have focused on market forecasting and trading applications. This article presents an overview of these studies. The specific purposes of the article are twofold: first, to review a representative group of SC applications in market forecasting and trading rules so as to document their unique characteristics as application areas; and second, to document the extent to which SC technologies have been employed.

Market Forecasting

Market forecasting involves projecting such things stock market indexes, like the Standard and Poor's (S&P) 500 stock index, Treasury bill rates, and net asset value of mutual funds. The role of SC in this case is to use quantitative inputs, like technical indices, and qualitative factors, like political effects, to automate stock market forecasting and trend analysis. This section provides an overview of representative SC studies in this area.

Kuo et. al. (1996), recognized that qualitative factors, like political effects, always play a very important role in the stock market environment, and proposed an intelligent stock market forecasting system that incorporates both quantitative and qualitative factors. This was accomplished by integrating a NN and a fuzzy Delphi model[3]; the former was used for quantitative analysis and decision integration, while the later formed the basis of the qualitative model. They applied their system to the Taiwan stock market.

Aiken and Bsat (1999) use a FFNN trained by a genetic algorithm (GA) to forecast three-month U.S. Treasury Bill rates. They conclude that an NN can be used to accurately predict these rates.

Thammano (1999) used a neuro-fuzzy model to predict future values of Thailand's largest government-owned bank The inputs of the model were the closing prices for the current and prior three months, and the profitability ratios ROA, ROE and P/E. The output of the model was the stock prices for the following three months. He concluded that the neuro-fuzzy architecture was able to recognize the general characteristics of the stock market faster and more accurately than the basic backpropagation algorithm. Also, it could predict investment opportunities during the economic crisis when statistical approaches did not yield satisfactory results.

Tansel et. al. (1999) compared the ability of linear optimization, NNs, and GAs to model time series data using the criteria of modeling accuracy, convenience and computational time. They found that linear optimization methods gave the best estimates, although the GAs could provide the same values if the boundaries of the parameters and the resolution were selected appropriately, but that the NNs resulted in the worst estimations. However, they noted that non-linearity could be accommodated by both the GAs and the NNs and that the latter required minimal theoretical background.

[3] See Bojadziev and Bojadziev (1997: 71) for a discussion of fuzzy Delphi method.

Kim and Han (2000) used a NN modified by a GA to predict the stock price index. In this instance, the GA was used to reduce the complexity of the feature space, by optimizing the thresholds for feature discretization, and to optimize the connection weights between layers. Their goal was to use globally searched feature discretization to reduce the dimensionality of the feature space, eliminates irrelevant factors, and to mitigate the limitations of gradient descent. They concluded that the GA approach outperformed the conventional models.

Abraham et. al. (2001) investigated hybridized SC techniques for automated stock market forecasting and trend analysis. They used principal component analysis to preprocess the input data, a NN for one-day-ahead stock forecasting and a neuro-fuzzy system for analyzing the trend of the predicted stock values. To demonstrate the proposed technique, they analyzed the 24 months stock data for the Nasdaq-100 main index as well as six of the companies listed therein. They concluded that the forecasting and trend prediction results using the proposed hybrid system were promising and warranted further research and analysis.

As a follow-up to Kuo et. al. (1996), Kuo et. al. (2001) developed a GA-based FNN (GFNN) to formulate the knowledge base of fuzzy inference rules, which can measure the qualitative effect (such as the political effect) in the stock market. The effect was further integrated with the technical indexes through the NN. Using the clarity of buying-selling points and buying-selling performance based on the Taiwan stock market to assess the proposed intelligent system, they conclude that a NN based on both quantitative (technical indexes) and qualitative factors is superior to one based only on quantitative factors.

Trading Rules

If one dollar were invested in 1926 in 1-month U.S. Treasury bills, it would have grown to $14 by December 1996. If that dollar had been invested in the S&P 500, it would have grown to $1,370 during that period. If the dollar had been invested with monthly switching to either Treasury bills or the S&P 500, whichever asset would perform the best during that month, it would have grown to over $2 billion dollars during that period.[4] Timing clearly is relevant and it is not surprising that trading rules have evolved that purport to optimize buy/sell timing decisions.

Of course, the extent to which timing is feasible is controversial. Sharp (1975) was skeptical that market timing could be profitable and Droms (1989) concluded that successful timing requires forecasting accuracy beyond the ability of most managers. Nonetheless, researchers continue to explore and enhance trading rules, driven, in large part, by the expanding technology. The goal of SC, as it pertains to trading rules, is to create a security trading decision support systems, which, ideally, is fully automated and triggered by both quantitative and qualitative factors. This section provides an overview of representative SC studies in this area.

Kosaka et. al. (1991) demonstrated the effectiveness of applying FL and NNs to buy/sell timing detection and stock portfolio selection. They reported that in a test of

[4] Kassicieh et. al. (1998, p. 122) and Farmer and Lo (1999, p. 9991).

their model's ability to follow price trends, it correctly identified 65% of all price turning points.

As a follow-up study, Kassicieh et. al. (1998) used the same GA with different data transformation methods applied to economic data series. These methods were the singular value decomposition (SVD) and principal component NN with 3, 4, 5 and 10 nodes in the hidden layer. They found that the non standardized SVD of economic data yielded the highest terminal wealth for the time period examined.

Baba et. al. (2000) used NNs and GAs to construct an intelligent decision support system (DSS) for analyzing the Tokyo Stock Exchange Prices Indexes (TOPIX). The essential feature of their DSS was that it projected the high and low TOPIX values four weeks into the future and suggested buy and sell decisions based on the average projected value and the then-current value of the TOPIX. To this end, they construct an (8, 15, 2) FFNN using a hybrid weight-training algorithm that combines a modified BP method with a random optimization method. Initially, the buy-sell decision was on an all-or-nothing basis; subsequently, using the GAs, an algorithm was developed for buying or selling just a portion of the shares. They conclude that NNs and GAs could be powerful tools for dealing with the TOPIX.

Comment

The purpose of this study has been to explore the extent to which hybrids of the SC technologies have been used to develop market forecasts and trading rules and to document the manner in which the SC technologies were implemented. Based on these studies, there is ample evidence that hybrids of the SC technologies have made inroads into these areas. As we improve our understanding of the strengths and weaknesses of these technologies and improve the manner by which we leverage their best features, it seems inevitable that they will become one of our important tools for developing market forecasts and trading rules.

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