

Neural Network Applications in Stock Market Predictions - A Methodology Analysis

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Abstract

Neural networks (NNs), as artificial intelligence (AI) methods, have become very important in making stock market predictions. Much research on the applications of NNs for solving business problems have proven their advantages over statistical and other methods that do not include AI, although there is no optimal methodology for a certain problem. In order to identify the main benefits and limitations of previous methods in NN applications and to find connections between methodology and problem domains, data models, and results obtained, a comparative analysis of selected applications is conducted. It can be concluded from analysis that NNs are most implemented in forecasting stock prices, returns, and stock modeling, and the most frequent methodology is the Backpropagation algorithm. However, the importance of NN integration with other artificial intelligence methods is emphasized by numerous authors. In spite of many benefits, there are limitations that should be investigated, such as the relevance of the results, and the "best" topology for the certain problems.

Keywords: *neural networks applications, stock market, qualitative comparative analysis, NN methodology, benefits, limitations*

1. Introduction

Because of their ability to deal with uncertain, fuzzy, or insufficient data which fluctuate rapidly in very short periods of time, neural networks (NNs) have become very important method for stock market predictions [7]. Numerous research and applications of NNs in solving business problems has proven their advantage in relation to classical methods that do not include artificial intelligence. According to Wong, Bodnovich and Selvi [10], the most frequent areas of NNs applications in past 10 years are production/operations (53.5%) and finance (25.4%). NNs in finance have their most frequent applications in stock performance and stock selection predictions. Many articles on NN applications in stock markets are concerned on individual methods applied, but there are no standardized paradigms that can determine the efficiency of certain NN methods in some problem domains [5]. The purpose of this paper is to identify the

main benefits and limitations of previous methods in NN applications in stock markets and to emphasize the problems that can be important for further research in this area. After a comparative analysis of methodology in previous research in relation to problem domains, data models and results criteria, some benefits and limitations emphasized.

2. Methods

According to many authors, NN methodology underestimates the design of NN architecture (topology), and methods of training, testing, evaluating, and implementing the network [13]. Since the data regarding the evaluation and implementation phase were not available in all analyzed articles, the paper is focused on NN architecture, training and testing. Design of NN architecture consists of the choice of the NN algorithm, the structure (number of layers, and number of neurons in the layers), the input and output functions, and the learning parameters [13]. As the first step, a qualitative comparative analysis of NN methodology in scientific journal articles concerned with NN applications in stock markets was conducted. NN methodology was analyzed in relation to specific problem domains of NN applications, data models used, and results obtained. It is assumed that those criteria include main characteristics of NN applications. However, the analysis could be made more effective by including additional criteria and statistical analysis, such as cluster of factor analysis that could indicate some hidden characteristics and connections between methodology, problems, and the results. The next step was to use the results of comparative analysis to identify the most efficient methodology for certain problems and to find new possibilities for NN applications that can improve limitations. The two main purposes that author aimed to accomplish in this research are to find out if there is any “recipe” for the efficient use of NN methodology in certain problem domains, and what are the main directions for NN future research in the area of stock market applications.

To provide the above analysis, three database indexes were searched: INSPEC, Applied Tech & Science Index and ABI/Inform, by using the keywords “neural+network+stock”. Search results consisted of 28 citations in ABI/Inform, 155 citations in INSPEC and 1 citation in Applied Tech & Science Index (total 184 articles). Research includes papers published since 1990. Because of the large number of articles related to the topic under investigation, 12 most representative have been included in the analysis. Therefore, the results should be taken cautiously.

3. Results

3.1. Comparative Analysis of NN methodology

The comparative analysis conducted in this study includes the analysis of NN methodology in relation to: (1) problem domain of the applications, (2) data model used in applications, and (3) results obtained using NN in stock markets.

3.1.1 NN methodology in relation to problem domain

Analysis of the problem domains of NN applications in previous research has shown that there are three main groups of problems that NN applications frequently deal with. First group consists of predicting stock performance by trying to classify stocks into the classes such as: stocks with either positive or negative returns [4, 8, 9] and stocks that perform well, neutrally, or poorly. Such NN applications give valuable support to making investment decisions, but do not specify the amount of expected price and expected profit. More information is given by the next group of frequently used applications: NNs for stock price predictions [3, 7]. Such systems try to predict stock prices for one or more days in advance, based on previous stock prices and on related financial ratios. The third important group of NN applications in stock markets is

concerned with modeling stock performance and forecasting [6, 12]. Such applications are not only focused on the prediction of future values, but also on the factor significance estimation, sensitivity analysis among the variables that could impact the result, and other analyses of mutual dependencies (including portfolio models, and arbitrage pricing models). The last group of applications frequently exists in NN research recently, although there are other, not so frequent problem domains.

In order to discover the connections between the problem domain and NN methodology used in the experiments, NN architectures are compared in relation to problem domains. Table 1 shows the NN algorithms and structures used in different applications in relation to problem domain. As can be seen in the table, the Backpropagation algorithm is the most common NN architecture, although other algorithms are used in some applications. The three-layer structure seems to be more effective according to many authors, with the exception of two applications [6,7] where the four-layer structure outperforms other structures.

Table 1. NN algorithm and structure according to problem domain

Problem domain	NN architecture	
	Algorithm	NN structure
Predicting stock performance (classification)	Backpropagation [8] Backpropagation [9] Boltzman machine [4]	2,3, and 4 layers (9-3-3-2) ¹ [8] 6 feedforward networks [9] 2 layers (88-1) [4]
Stock price predictions	Backpropagation [3] Backpropagation [7] Perceptron [7], ADALINE / MADALINE [7]	3 layers (24-24-1) [3] 4 layers (10-10-10-1) [7] 2 layers (40-1) [7] 2 layers (40-1) [7]
Modeling the stock performance (ANN combined forecasts)	Backpropagation [6] Hybrid approach (Backpropagation NN + expert system) [12]	4 layers (3-32-16-1) [6] 3 layers (4-7-2) [12]

Furthermore, the Table 1 also shows that a hybrid approach is used in modeling the stock performance, while individual NN algorithms are used in other problem domains.

The next characteristic of NN methodology that should be compared with the problem domains is NN's learning function. It is found that majority of applications use the sigmoid transfer function, with changeable learning parameters α and η , that are optimized in the experiments. An important trend in the applications is combining two or more NNs into a single NN system, or incorporating other artificial intelligence methods into a NN system, such as expert systems, genetic algorithms, natural language processing. The number of Kohonen's, Hopfield's, and other algorithms is relatively small in the stock market NN applications. This could be caused by the convenience of the NN algorithms for classification rather than prediction [13], although some researchers suggest the investigation of those and other algorithms in stock market applications as a guideline for further research [7,12].

3.1.2 NN methodology in relation to data model

After a brief overview of the articles, it was evident that almost all applications of NN in stock markets are based on a different data model. In order to see if there are similarities among

various data models that are used with certain NN architectures, it was necessary to observe the NN algorithms, structure and learning functions in relation to data models. Because the design of a data model for an NN is determined mostly by the choice of input and output variables [13], four characteristics of data model are observed: the number of input variables, the names of input variables, number of output variables, and names of output variables. The comparison is shown in Table 2.

Table 2. NN algorithms in relation to data models

NN application	NN algorithm	DATA MODEL			
		Number of input variables	Input variables	Number of output variables	Output variables
predicting stock performance [8]	Backpropagation	9	– recurring themes in president's letter to stockholders (qualitative data)	1	stock performance (possible values: - well - poor)
recommendation for trading [9]	several NN + set of rules	3	– open price of S&P 500 stock index – low price of S&P 500 stock index – close price of S&P 500 stock index	1	recommendation (possible values: - long - short)
classification of stocks [4]	Boltzmann machine	88	– 14 company financial ratios, – 14 relative ratios of current-to-mean financial ratios, – 20 features of relative performance of 5 financial ratios to respective industry benchmarks, – 35 year-over-year % change for each macroeconomic factor	1	stock return (possible values: - positive - neutral - negative)
predicting price changes of S&P's 500 Stock Index [3]	Backpropagation	24	– monthly growth rate of the aggregate supply of money, M-1 – change in and volatility of S&P and Gold futures prices: Barron's weekend closing prices, derived month end price, standard deviation of prices for each month (centered mean and weekend closing prices) – end-of-month net % commitments of large speculators, large hedgers, and small traders	1	change of the monthly centered price mean for the forecasted month
stock price prediction [7]	Backpropagation, Perceptron, ADALINE / MADALINE	40 (10 for Backpropagation)	– current stock price. – the absolute variation of the price in relation to previous day. – direction of variation, – direction of variation from two days previously, – major variations in relation to the previous day – the prices of the last 10 days (for Backpropagation)	1	stock price for the various periods in days

NN application	NN algorithm	DATA MODEL			
		Number of input variables	Input variables	Number of output variables	Output variables
modeling the stock performance [6]	Backpropagation	3	Variables are not named. Symbols used: – A – B – C	1	Variable not named: Y
forecasting the performance of stock prices [12]	hybrid approach (Backpropagation + expert system)	4	4 financial ratios: – current ratio (CR), – return on equity (ROE), – price/equity (P/E), – price/sales (P/S)	2	Well performing Poor performing

As illustrated in the Table 2, the researchers have used various data models, and no model can be considered as the predominant. This variety could cause the difficulties in constructing a paradigm of NN efficiency. The number of input variables ranges from 3 [9] to 88 [4]. However, majority of variables are the stock prices (such as open, high, close, etc.), and financial ratios (such as price/equity ratio, current ratio, etc.). All researchers, except Swales and Yoon [8] have been used quantitative data, mostly from the same sources: stock market indexes (S&P, Dow Jones, etc.) or Fortune 500 and Business Week Top 1000 [12]. Using qualitative data is the new approach to NN applications and opens the possibilities for further research.

The structure of NNs in applications is not presented in the Table 2. However, it is implied in the data model. since data model determines the number of input and output neurons. The number of hidden layers, and the numbers of neurons in hidden layers, is larger if the number of input data is larger too.

The relation between NN learning functions and data models is clearer: most researchers use the sigmoid learning function. Important information for the data model can be the size of the training set in each application. The size of the training sets in applications is often over 100, and it depends on the predicted time period. Therefore, the set is larger in applications that try to predict 10, 20, 30, or more periods in advance [7]. Some researchers [3] emphasize that size of training set is critical because of the possible hidden correlations among the data.

3.1.3 NN methodology in relation to results

In most analyzed applications, the NN results outperform statistical methods, such as multiple linear regression analysis [6], discriminative analysis [8] and others. The accuracy rate of NN systems ranges from 68 % to 90% [7]. In some articles, the exact values of accuracy rates were not available. Table 3 shows the distribution of NN systems' correctness in relation to the NN algorithm used.

Table 3. NN algorithms in relation to results obtained in applications

Results	NN applications	NN algorithms	NN structure
outperforming statistical methods	stock performance modeling [6], predicting stock performance [8]	Backpropagation [6,8]	3-32-16-1 [6] 9-3-3-2 [8]
correctness 90-100%	stock price prediction [7]	Backpropagation [7]	10-20-1 [7]
correctness 80-90%			
correctness 70-80%	stock price prediction [7] classification of stocks [8] predicting stock performance [8]	ADALINE/MADALINE [7] Boltzmann machine [4] Backpropagation [8]	40-1 [7] 88-1 [4] 9-3-3-2 [8]
correctness 60-70%	stock price prediction [7]	Perceptron [7]	40-1 [7]

It can be concluded from Table 3 that NN accuracy mostly ranges from 70 to 80 %. Although the risk for using NNs is still relatively high, NNs outperform statistical methods for a 5 - 20 % higher accuracy in rate [6,8]. It is also evident that the Backpropagation algorithm has a higher accuracy rate than other NN algorithms, and that Perceptron is the least accurate algorithm. However, researchers who combined NN with expert systems did not mention the percentage of NN correctness [9,12]. Therefore, those applications cannot be compared with others, although the authors claim that NNs, if combined with expert systems, perform at a higher accuracy rate than alone [9,12].

3.2 Benefits and limitations of NN methodology

3.2.1 Benefits

Most of the benefits in the articles depend on the problem domain and the NN methodology used. A common contribution of NN applications is in their ability to deal with uncertain and robust data. Therefore, NN can be efficiently used in stock markets, to predict either stock prices or stock returns.

It can be seen from a comparative analysis that the Backpropagation algorithm has the ability to predict with greater accuracy than other NN algorithms, no matter which data model was used. The variety of data models that exist in the papers could also be considered a benefit, since it shows NNs flexibility and efficiency in situations when certain data are not available. It has been proven that NN outperform classical forecasting and statistical methods, such as multiple regression analysis [9] and discriminant analysis. When joined together, several NNs are able to predict values very accurately, because they can concentrate on different characteristics of data sets important for calculating the output. Analysis also shows the great possibilities of NN methodology in various combinations with other methods, such as expert systems. The combination of the NN calculating ability based on heuristics and the ability of expert systems to process the rules for making a decision and to explain the results can be a very effective intelligent support in various problem domains [12].

3.2.2 Limitations

Some of the NN limitations mentioned in the analyzed articles are: (1) NNs require very large number of previous cases [4, 12]; (2) "the best" network architecture (topology) is still unknown [7]; (3) for more complicated networks, reliability of results may decrease [12]; (4) statistical relevance of the results is needed [7]; and (5) a more careful data design is needed [6]. The first limitation is connected to the availability of data, and some researchers have already proven that it is possible to collect large data sets for the effective stock market predictions, e.g. Schoeneburg used the input data of 2000 and 3000 sets [7]. The limitation still exists for the problems that do not have much previous data, e.g. new founded companies. The second limitation still does not have a visible solution in the near future. Although the efforts of the researchers are focused on performing numerous tests of various topologies and different data models, the results are still very dependent on particular cases. The third limitation, concerning to the reliability of results, requires further experiments with various network architectures to be overcome. The problem with evaluating NN reliability is connected with the next limitation, the need for more complex statistical relevance of the results. Finally, the variety of data models shows that data design is not systematically analyzed. Almost every author uses a different data model, sometimes without following any particular acknowledged modeling approach for the specific problem.

There are some other limitations, concerning the problems of evaluation and implementation of NN, that should be discussed in order to improve NN applications.

4. Discussion

4.1 Conclusion

Rapid growth of information technology including Internet and other ways of telecommunication contributes to fast development of computer science methods. Therefore, this research could not accurately present the situation in NNs applications in stock markets. Large number of research is done and implemented by companies that are not published in scientific indexes analyzed. However, it can be concluded from previous research that: (1) NNs are efficiency methods in the area of stock market predictions, but there is no "recipe" that matches certain methodologies with certain problems; (2) NNs are most implemented in forecasting stock prices and returns, although stock modeling is very promising problem domain of its application; (3) most frequent methodology is the Backpropagation algorithm, but the importance of integration of NN with other artificial intelligence methods is emphasized by many authors; (4) benefits of NN are in their ability to predict accurately even in situations with uncertain data, and the possible combinations with other methods; (5) limitations have to do with insufficient reliability tests, data design, and the inability to identify the optimal topology for a certain problem domain.

4.2 Guidelines for further research

The authors emphasize the necessity for including more data in the models, such as other types of asset; more financial ratios; and qualitative data. Furthermore, the recommendation for the use of various time periods occurs frequently. Stocks are commonly predicted on the basis of daily data, although some researchers use weekly and monthly data [3]. Additionally, future research should focus on the examinations of other types of networks that were rarely applied, such as Hopfield's, Kohonen's, etc. Finally, almost all researchers emphasize the integration of NNs with other methods of artificial intelligence as one of the best solutions for improving the limitations.

Since NNs are relatively new methods and still not adequately examined, they open up many possibilities for combining their methods with new technologies, such as intelligent agents, Active X, and others. Those technologies could help in intelligent collecting of data that includes searching, selecting, and designing the large input patterns. Furthermore, with its intelligent user interfaces, those methods could improve the explanation of NNs results and their communication with user. NNs researchers improve their limitations daily, and that is the valuable contribution to their practical importance in the future.

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ⁱ Numbers in the brackets denote the number of neurons in each layer, e.g., 9-3-3-2 denotes that the first layer consists of 9 neurons, the second layer of 3 neurons, the third layer of 3 neurons and the fourth layer of 1 neuron. If the structure of layers is missed, the author in original paper didn't mention it.