3. Neural Networks in Finance and Investments – Analysis of Previous Research

In order to set the starting point of our research it was necessary to classify the problems and models used in the previous research on NN applications on stock market predictions, and to identify the main benefits and limitations of previous results. To provide the comparative analysis of the previous research, 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 (a total of 184 papers). The research includes papers published since 1990.

3.1. Classification of Problems in NN Application in Finance and Investing

Finance and investing are one of the most frequent areas of NN applications. Some of the most representative problems being solved by NNs are bankruptcy predictions, risk assessments of mortgage and other loans, stock market predictions (stock, bond, and option prices, capital returns, commodity trade, etc.), financial prognoses (returns on investments) and others. Chase Manhattan Bank (Marose, 1990), Peat Marwick, American Express (Zahedi, 1993) are only a few of many companies that efficiently apply NNs in solving their financial and investing problems.

Numerous research and applications of NNs in business have proven their advantage in relation to classical methods that do not include artificial intelligence. According to Wong et al. (1997), the most frequent areas of NN applications in past 10 years are production/operations (53.5%) and finance (25.4%). NNs in finance have their most frequent applications in predicting stock performance and selecting stocks for trading on stock markets. Many articles on NN applications on stock markets apply only one NN algorithm although there are no standardized paradigms that can determine the efficiency of certain NN algorithms and architectures in particular problem domains (Li, 1994). Some authors, such as Zahedi (1997), have emphasized the most frequent problems in finance exploited by NNs. Using a meta-analysis, the author extracted the following problem groups where NNs were mostly used in:

- Loan assessment:
  - mortgage lending (Collins et al., 1988/93),
  - forecasting the loan risk category as good, criticized, or charge-off (Marose, 1990/93),
  - underwriting loans and insuring mortgage loans (Malhotra et al.,1994),
- Stock and bond market:

  a) Timing trade
  - deciding when to trade on S&P 500 (Trippi, De Sieno, 1992),
  - deciding when to buy and sell stocks (Kimoto, Asakawa, Yoda, and Takeoka, 1990/93),
  - problem of buying and selling orders (Bergerson and Wunsch, 1991/93),
  - discovering triangle patterns in stock prices on the stock exchange (Kamijo and Tanigawa),
  - recognizing buying and selling patterns of the live-cattle commodity futures markets (Collard, 1993),

  b) Risk rating and classification
  - bond rating (Dutta and Shekhar, 1988/93),
  - bond classification (Surkan and Singleton, 1990/1993),
  - classification of stock returns into high or low performance (Yoon and Swales, 1992, 1996),

  c) Forecasting the market
  - prediction of stock prices (Schoeneburg, 1990),
  - forecasting futures market prices (Grudnitski and Osborn, 1993),
  - prediction of monthly stock price movements (E.Y.Li, 1994),
  - stock market prediction (Kimoto and Asakawa, 1990),

  d) Forecasting returns
  - testing market efficiency – prediction of stock returns (White),
  - problem: prediction of stock returns (Wong and Long, 1995).

When we focus the analysis onto the stock markets, it can be synthesized that there are three main groups of problems that NN applications frequently deal with. The first group consists of predicting stock performance by classifying stocks into the classes of stocks such as: positive return stocks and negative return stocks (Kryzanowski et al., 1993; Swales and Yoon, 1992, 1996; Trippi and DeSieno, 1992) or classes of stocks that perform well, neutrally, or poorly. Such NN applications give valuable support in making investment decisions, but do not specify the amount of the expected price and the expected profit. More information is given by the next group of frequent applications: NNs for stock price predictions (Schoeneburg, 1990; Grudnitzky and Osburn, 1993). Such systems try to predict stock prices for one or more days in advance, based on previous stock prices and related financial ratios. The third important group of NN applications on stock markets is concerned with modeling stock performance and forecasting (Refenes et al., 1994; Yoon et al., 1994). 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 exists frequently in NN research, although there are other, not so frequent problem domains.

Despite the wide usage of NNs in finance and investing, there are still some open questions and guidelines for further research in the above problem domains, which will be discussed later in the text. Our research will focus on prediction of individual stock returns, which is an investment problem. In order to define the models that will be tested, the most representative financial models for stock return prediction are identified.

3.2. Representative Financial Models Used

One of the main difficulties in forecasting techniques, as well as in NNs is to choose the right model. Although NNs are not strictly model dependent, theoretical models serve as the basic framework for selecting the input variables. Previous research on NN applications used either univariate models of historical stock prices in order to find the evidence against the Efficient Market Hypotheses (White, 1997), or mainly followed Fundamental Analysis by testing stock behavior on the basis of selected variables from company's balance sheets and income statements (Yoon et al., 1994, Chenoweth et al., 1997, Kryzanowski, et al., 1997, and others). Maturi (1993) counts over a hundred economic theories for predictions on stock markets. Some of them are focused on portfolios such as Markowitz Expected Return-Variance Model, Capital Market Equilibrium Theory (CMT) or on the large group of stocks such as Dow Theory, and some of them are focused on individual stocks performance such as Technical model. They try to predict on the basis of economic cycles such as Kondratieff Wave, Sunspot Phenomena, Bragg Economic Series Theory, Elliot Wave, Fibonacci Connection, or on the basis of computed indicators such as Index of Leading Indicators, MACD indicator, etc. Then, there is the Time Based Predictors Theory, which assumes that it is possible to find best days of the week, best month of the year, best Pre-Holiday trading days or other time-based predictors for stock market prices and return. Event Factors Theory, also tested with NNs (Guimaraes, et al., 1994) determines the influence of specific events on future stock market prices. Some of the events are analyst recommendations, merging and takingover, corporate spinoffs, stock splits, and sunspot indicators and others.

There is a number of existing economic theories on stock markets, and we have focused our research on those of them that deal with prediction of individual stock return as the output variable. Furthermore, since NNs are quantitative methods we will not discuss or use qualitative forecasting methods such as Delphi method or scenario theories.

First, the Theory of Market Efficiency will be explained since it is some kind of an anti-model, which states that any prediction on stock market on the basis of historical data is impossible. All the other models, such as Technical model, Black-Scholes, Capital Assets Pricing Model and others, aimed to prove the opposite, with more or less success, until a well structured Arbitrage Pricing Theory (Factoral model) came in front. Factoral model not only provided the strong evidence against the Efficient Market Hypothesis, moreover made it only a special case (Refenes et al., 1997). After the Theory of Market Efficiency description of the four economic theories tested in our research follows.

Theory of Market Efficiency

Theory of Market Efficiency or Efficient Market Hypotheses (EMH) or Random Walk Theory (made popular in 1973 by Burton G. Malkiel) "implies that all public information on future price movement for a tradable asset has already been incorporated in its current price, and that therefore it is not possible to earn economic profits by trading on this information set." (Refenes, et al., 1997). Statistically it implies a "random walk" model. The basis for Random Walk on stock markets Malkiel finds in three reasons (Maturi, 1993):

1) a very rapid response of the efficient market to the new information,
2) if the stock prices reflect all available information, it is impossible to use that information to predict the market,
3) the market cannot be predicted except by chance.

Historical prices and patterns according to this theory have no influence on future price direction. Furthermore, all information from company's balance sheets and income statements are also already incorporated in the present stock price. Since future movement of such information is random, it cannot be used to earn more than average return.

Weakness of this theory is that it assumes all publicly available information incorporated in the present stock price, but the prediction using publicly unavailable information is not ruled out. Although it does not take into account available information, it does take risk into account. The Random Walk theory sets the risk-taking strategy for investing on stock markets. According to that strategy a portfolio theory is built, stating that the expected return of a portfolio is equal to the expected return of individual securities multiplied by their proportion, minus the expected risk.

$$R_p = \sum_{i=1}^{N} w_i \overline{r_i} - \sqrt{\sum_{i=1}^{N} w_i^2 \sigma_i^2 + e \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} w_i w_j \rho_{ij} \sigma_i \sigma_j}\,, \qquad (3.1)$$

where R_p is the expected return of the portfolio, w_i is the proportion of individual security in the portfolio, $\overline{r_i}$ is the expected return of individual securities in the portfolio, σ_i is the standard deviation of each security, and ρ_{ij} is the correlation between standard deviations of each pair of securities. After conducting some empirical experiments in which traders did make profits based on this strategy, the Theory of Market Efficiency was disturbed. Its disadvantage was in the fact that it was based on the assumption that minor departures from randomness are not significant (thus the statistical tests could not reject this hypothesis). However, it is proved in the end of 1980s that those minor departures were significant for trading profits (Refenes, et al., 1997). The Efficient Market Hypothesis was finally abandoned when econometric tests specified a more general structural model for prediction of assets returns. Such model includes autoregressive terms and other variables that influence asset, and makes EMH only a special case that appears when autoregressive terms are equal to 1 and all the other variables are equal to 0. Statistical tests of this model in capital markets show that EMH can be rejected for almost all the major stock markets. Applied in finance, structural theory grew into Arbirtage Pricing Theory (or Factoral Model) that will be described later in the text.

Peters (1994) tested Efficient Market Hypothesis against Hurst processes (or biased random walks) on stock markets. He emphasized that stability of stock markets depends on the diversity of investors. The major technique that Peters uses is the fractal or rescaled range (R/S) analysis for uncovering long memory effects, fractal statistical structure, and the presence of cycles. The results on the long-time period show the stable existence of the Hurst process for the four year-cycles and longer, with the weak evidence of the 40-day cycle. The short-time period results (intra-day data) showed no high-frequency intra-day cycles. It can be concluded from Peter's research that there are no deterministic cycles at high frequency data and the global structure is apparent only by observing the lower frequencies of data. These results can be chalenging for testing NNs on high-frequency data (daily stock returns) in order to see their efficiency with noiseness.

Some research has been done on testing NNs against the EMH using univariate time-seria of stock return (White, 1997). The author aimed to predict a one-day rate of return on the IBM common stock, using the following formula for calculating the one-day return:

$$R_t=(p_t-p_{t-1}+d_t)/p_{t-1} \quad , \qquad (3.2)$$

where p_t is the closing price on day t, d_t is the dividend paid on day t. Without much success, White tried to find the evidence against the efficient market hypothesis by proving the existence of nonlinear relationships in stock return movement. In his experiment, NN obtained lower test correlation than the linear model, although the training results were optimistic. Such failure of NNs could be caused by overfitting. However, White's experiment showed the extremely rich dynamic behavior of NN. The limitation of White's results is in a weak NN methodology used (only Backpropagation, without advanced optimizing techniques). As guidelines for further research, White suggests the additional input variables for the model such as: volume, other stock prices and volume, leading indicators, macroeconomic data, etc., and recurrent connections in NN. He also suggests using more output variables: two-day, three-day return, or prices of other assets, and using the data within a one-day period. Global optimization methods such as simulated annealing and genetic algorithms are proposed as additional methods for obtaining the global optimum. For NN evaluation, the author suggests the profit that NN generates from trade, not an RMS error. Many of the White's guidelines are included in our experiments, although our aim was not to test the EMH, but other theories. Instead limiting to the historical univariate time series, we included other variables in the model, and used more diversified and more improved NN methodology.

3.2.1. Technical Model

The Technical model is derived from technical analysis, a wide framework of analytical measures based on historical data on stock prices. It can be applied to aggregate as well as to individual securities. The foundation of technical analysis lies in two variables:

- historical prices of the stock,
- total volume of the stock transactions on the stock market.

Price and volume trends are graphically and computationally analyzed in order to find the future movements, as well as the trading opportunities. The mostly used formations are trendlines, averages, gaps, resistance and support levels. The theory is based on the assumption that the history will be repeated, and that the pattern derived from historical data can help predicting the future.

3.2.2. Black-Scholes Formula

The model was created by Fisher Black and Myron Scholes in 1973 (Maturi, 1993) and differed from the other models of that time in its focusing on stock price and interest rates variables rather than on risk expectations. They introduce a calculation-consuming formula with the following three input variables:

- stock price,
- interest rates,
- stock price volatility,

which results in the trading decision according to the following decision rule:

- buy if the market price is less than the formula price,
- sell if the market price is greater than the formula price.

The model had a great success on option market in the 1980s. Since none of the research tested Black-Scholes model using NNs, it was a challenge to test whether this theory is efficient on stocks and how NNs can approximate this formula.

3.2.3. Capital Asset Pricing Model (CAPM)

Created by William Sharp and John Lintner in 1960s (Maturi, 1993), CAPM describes the behavior of security returns on efficient markets by focusing on risk elimination. An assumption is that the stock risk consists of two different parts – market risks and non-market risks. The rate of return on stock is computed according to the formula:

$$RR = RFR + \beta \ (MR), \tag{3.3}$$

where RR is the rate of return, RFR is the risk-free rate (US Treasury Bills are often used as an example of the risk-free rate), and MR is the market return risk-free rate.

Market risk is presented by the variable β (beta). "Beta is the measure of the price volatility of a specific stock in comparison to the overall market" or the degree of stock volatility in relation to market (Maturi, 1993). Value Line Investment Survey calculates beta using weekly price changes of a stock and weekly percent changes in the NYSE

Composite Index over the past five years. Since we use daily data in our experiment, the another formula for β is applied, according to Maturi (1993):

$$\beta = \frac{expected\ \ stock\ \ return}{total\ \ return\ \ on\ \ market\ \ index}, \tag{3.4}$$

where S&P 500 can be used as the market index. Since some scientific research (Fama and French, 1992) show that there is no link between beta and long-term performance of the stock, we use this model in our experiments for predicting the short-term (daily) stock return. CAPM ignored transaction costs and income tax. In spite of that, the model has well portrayed market behavior over the years.

3.2.4. Arbitrage pricing theory (or Factoral model)

The theory states that stock return can be explained in terms of a set of factors (Refenes et al., 1997). A traditional assumption is that stock return is a linear combination of these factors, according to the formula:

$$R_i = \alpha_i + \sum_{j=1}^{n} x_j \beta_{ij} + \varepsilon_i\ , \tag{3.5}$$

where R_i is the return on stock *i,* α_i is a constant for stock *i*, x_j is the determinant factor, β_{ij} is the return on stock *i* attributable to factor *j*, and ε_i is the random error with zero mean. This theory considers the Market Efficient Hypothesis only as a special case when it turns out that none of the factors is statistically significant for an asset. The factors are mostly derived from the fundamental analysis, which uses company's financial ratios from the balance sheets and income statements, then macroeconomic factors and all relevant public information.

The shortcoming of this model is that it does not identify the number of factors or the definition of factors that influence the assets (Ahmadi, 1996). Refenes et al. (1997) tested the Factoral model on hourly volatility forecasting using Backpropagation NN, Box-Jenkins ARIMA procedure and multiple regression, and showed that NNs outperforms Box-Jenkins and multiple regression methods. However, the performance of NNs was not very high (correlation between the desired and the actual output was 0.676 for NNs, 0.635 for multiple regression, and 0.58 for Box-Jenkins). In order to test the efficiency of the

Factoral model on the daily stock return prediction, we test the same statistical methods, but using a wider set of NN architectures and more advanced optimization techniques.

How to Select Microeconomic (In-Company) Factors for the Factoral Model?

Because of the large number of factors that can serve as potential input variables, we have searched the literature in order to extract the most significant ones for our research. A detailed statistical analysis of the in-company factors that influence the assets is done by Rees (Rees, 1990). He claims that the problem of choosing the ratios causes many difficulties in the ratio analysis. It is important to select the most relevant elements of corporate performance, and also to statistically prove the effectiveness of the ratios. Two ways of selecting ratios exist in the previous research: (1) a traditional normative approach that tries to identify different aspects of decision-makers' interest and selects ratios that are relevant for those aspects, and (2) a statistical approach that analyzes the statistical relationships between ratios, such as clustering. First approach is also called an 'a priori' approach since it is based on prior experience. It often includes benchmark statistics for each ratio and ignores differences in business practice. Therefore, the results should be taken cautiously. Subjective classification and a lack of guidance are the additional disadvantages of this approach. Second, statistical approach aims to find the evidence for rejecting the ratios that do not provide additional information to the remaining ratios.

Courtis (1978, in Rees, 1990) suggested a financial ratio categorical framework that classifies ratios into three groups: profitability ratios, managerial performance ratios, and solvency ratios. The framework is able to fit 79 ratios into this format. Curtis mentions the problem of information redundancy that can appear in this frame, and suggests that such colinearity will enable analysts to select sub-sets of available ratios. Rees notes that some traditional sets of ratios have been established and accepted as suitable indicators of each characteristic of a firm performance. One of the most representative set is Datastream classification of 'Key Accounting Ratios' that identifies five groups of ratios as shown in Table 2 (Curtis, in Rees, 1990):

Table 2. Key accounting ratios according to Datastream classification

Group of ratios	Ratios
Profitability	Return on shareholders' equity
	Return on capital employment
	Trading profit margin
	Pre-tax profit margin
Turnover	Turnover/assets employed
	Stock turnover
	Debtor's turnover
	Creditors' turnover
Gearing	Capital gearing
	Income gearing
	Borrowing ratio
Liquidity	Working capital ratio
	Quick assets ratio
Productivity	Average salary per employee
	Sales per employee
	Operating profit per employee
	Capital employed per employee
	Stock and WIP per employee

Statistical relevance of factors that influence the average stock return is examined (using correlation, regression, and t-statistics) by Fama and French (1992). The authors test the joint impact of market β, size of the firm, leverage, and book-to-market equity (BE/ME) to average stock returns on NYSE, AMEX and NASDAQ stock markets. The results show a very weak relation between β and stock return in the period of 1941-1990 and by that put into question the basic prediction of the Sharpe-Lintner-Black (SLB) model that average stock returns are positively related to market β. One of the other findings about stock return shows that average return is in negative relation to firm size (Banz, 1981), in positive relation to leverage (Bhandari, 1988), also positively related to E/P (Earnings per share) (Basu, 1983), then positively related to book-to-market equity (BE/ME) for US (Stattman, 1980; Rosenberg et al., 1985) and Japanese stocks (Chan et al., 1992). The authors assumed that some of those variables are redundant, and found that firm size and book-to-market equity capture the cross-sectional variation in average stock returns observed in association with size, E/P, book-to-market equity, and leverage. However, the authors emphasize the importance of testing the relationships among size and book-to-market equity and other factors, in order to see if these findings will persist, and if they result from rational or irrational asset pricing. It is also valuable to test the size and book-to-market equity ability to describe the return through time.

Ezzamel et al. (in Rees, 1990) used cross-correlation statistics (product moment correlation and spearman correlation) to examine fifty-three ratios for over one thousand manufacturing companies. If the correlations between two ratios were closer to +- 1, ratios were supplemented. As a result, five to ten more prominent characteristics have been identified. Some of them are capital intensiveness, profitability, working capital position, liquidity, and asset turnover. As the extension to this approach, the authors suggested: (1) to conduct a more detailed analysis of relationship between various ratios, and (2) to examine predictive models that use financial information in order to choose the most useful ratios. The first suggestion includes one of the most frequent analysis for identifying patterns in financial ratios, called Factor Analysis or Principal Component Analysis (PCA) that generates linear combination of input variables in the way that the composite factors contain as much of the information content or variability as possible. This process is also called "data reduction". One category of information that can be obtained from the original data is represented by a factor. The variables in one factor that are highly correlated can be replaced by one of those variables called a surrogate. In the Rees' experiment, 20 original ratios for the 78 non-financial companies were grouped into three factors: productivity, return/gearing, and liquidity/turnover.

The stable statistical results are obtained by the research of Pinches et al. (1973, in Rees, 1990). They tested an empirically based classification and its stability over time. They conducted four separate cross-sectional tests and identified seven factors presented in Table 3 (Pinches et al., in Rees, 1990). The obtained factors show impressive stability of more than 0.9 in most of the factors.

Table 3. The most significant factors that influence the assets

Factor	Stability	Surrogate ratio	Loading
Return on investment	0.937	Net income / Net worth	0.965
Capital intensiveness	0.800	Sales / Total assets	0.875
Inventory intensiveness	0.678	Inventory / Sales	0.867
Financial leverage	0.985	Debt / Total capital	0.975
Receivables intensiveness	0.922	Receivables / Inventory	0.990
Short-term liquidity	0.937	Current assets / Liabilities	0.825
Cash position	0.866	Cash / Fund expenditures	0.935

However, according to Pinches et al., stability of results is an empirical question due to different sets of specifications of ratios, different industries and economic environments. The approach was further examined by Gombola and Ketz (1983, in Rees, 1990). They were focused on the cash flow variables and found that different factors can be generated when the inflation adjustment is made, but it does not imply any significant change in the factor patterns. Another experiment was done by Taffler and Sudarsanam (1979, in Rees, 1990), who analyzed 80 financial ratios for 525 quoted manufacturing companies and identified 9 factors that explain 93% of the variation in the total data set. Five of them; profitability, financial leverage, working capital position, asset turnover, and liquidity explain 81% of the data set. Pohlman and Hollinger (1981, in Rees, 1990) conducted canonical correlation focused on identifying the maximum amount of relationship between the two sets of variables, since Factor analysis tries to account as much of the variance as possible. They noted that original data do not contain sets that can be clearly distinguished. Chen and Shimerda (in Rees, 1990) investigated the principal component analysis based studies in order to see if some of the ratios can be reduced in a way that they become incorporated into other ratios. Although the researchers after five analyzed studies discovered that results differ, further examination on failure prediction data has shown that most of the previously untested ratios could be easily classified into the factors found by

Pinches et al. Because of such consistent finding of many authors, the selection of financial ratios obtained by Pinches et al. is used in our experiments.

NN researchers applied the experience of financial ratio analysts only partially. They mostly use their own combination of company ratios. In order to compare the successfulness of the previous research to the successfulness of our experiments, we will note some of the other authors' results. Kryzanowski et al. (1993) use a large number of 88 factors including 14 financial ratios consisting of profitability ratios, debt ratios, liquidity and activity ratios, and ratios that compare the performance of individual company to the group industry. Their results show that NNs are able to correctly classify 66.4% of cases into well or poor performing stocks. Ahmadi (1997) suggests that NNs can serve as the selector for significant factors, because the NN system is distribution free (probability distribution of the rate of returns need not be known in advance). Yoon et al. (1994) developed a hybrid rule-based and artificial neural network approach for determining company's stock performance by classifying it into a well performing or poor performing group. The input variables were:

- Current ratio (CR),
- Return on Equity (ROE),
- Price to Earnings (PE),
- Price to Sales (PS).

Feedforward Backpropagation NN is used as a knowledge base, with a 4-3-2 three-layer structure. The results of NN were then used to measure the relative strength between each input and each output variable, and the explanation is provided by the developed expert rules. After the training phase the system was tested on 75 companies. It is observed that results were improved by increasing the number of hidden units up till 7. After that number the NN shows decreasing in accuracy of prediction. The results of the interpretation method show that ROE is the most important factor for stock performance. PE and PS also have a positive influence while CR has a negative influence to stock performance.

The above description of the previous research shows that most of the authors choose financial factors on the basis of heuristics, and use NN as the selector. In our research a systematic modeling strategy is employed that will extract the best combination of factors using linear and nonlinear methodology.

How to Select Macroeconomic Variables for the Factoral Model?

Another set of factors, macroeconomic variables are also tested on stock return predictions, but with a very limited NNs methodology. In order to identify the important factors, we describe some of the other researchers' findings in the further text.

Chen et al. (1986) investigated the influence of economic state variables to stock market returns and assets pricing. They found that the most significant variables are:

- industrial production,
- changes in the risk premium, and
- twists in the yield curve.

The impact of unanticipated inflation and changes in the expected inflation also show some significance, but a weak one comparing to first three variables. Important finding is that stock market indices have insignificant influence on stock pricing (expected return), although they significantly influence the variability of stock returns. Next, the authors note that the consumption and oil price changes were not significant for the asset pricing.

Fang (1997) has found that a world market factor, a national market factor, and a foreign exchange risk factor affect common stock return cross-sectionally. According to Fang, the return is higher if the correlation between the common stock and the foreign exchange rate is negative.

Many other authors who did not use macroeconomic variables in their NN tests strongly recommend them in their guidelines for further research (White, 1997, Chenoweth and Obradovic, 1997, Yoon et al., 1997 and others). In our experiments we have used macroeconomic variables in the Factoral model.

Besides the above theories, comparative analysis of the previous research shows that there are some other variables frequently used in NN applications on stock markets. The selection of those variables is useful for defining our Factoral model variables.

3.2.5. Other Models and Variables Used in Predicting Stock Return

After a brief overview of the previous NN applications on stock market, it was evident that almost all applications are based on a different data model. Because the design of a data model for an NN is determined mostly by the choice of input and output variables (Zahedi, 1993), four characteristics of the data model are observed: the number of input variables, the names of input variables, the number of output variables, and the names of output variables. The comparison is shown in Table 4.

Table 4. NN algorithms in relation to data models

NN application	NN algorithm	DATA MODEL		
		No. of input varia-bles	Input variables	Output variables
stock price prediction (Schoeneburg, 1990)	Backpropa-gation, Perceptron, ADALINE / MADALINE	40 (10 for Back-propaga tion)	- current stock price. - absolute variation of the price in relation to previous day. - direction of variation, - direction of variation from two previous days, - major variations in relation to the previous day, - prices of the last 10 days (for Backpropagation)	stock price for the next day
recommendation for trading (Trippi and DeSieno, 1992)	several NNs + 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	trade recommendation: - long - short

NN application	NN algorithm	DATA MODEL		
		No. of input varia-bles	Input variables	Output variables
classification of stocks (Kryzanowski, Galler, and Wright, 1993)	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	stock return: - positive - neutral - negative)
predicting price changes of S&P's 500 Stock Index (Grudnitzky and Osburne, 1993)	Backprop	24	- monthly growth rate of the aggregate supply of money, M-1 - change and volatility of S&P and Gold futures prices: - end-of-month net % commitments of large speculators, large hedgers, and small traders	change of the monthly centered price mean for the forecasted month
forecasting the performance of stock prices (Yoon et al., 1994)	hybrid approach (Backprop + expert system)	4	4 financial ratios: - current ratio (CR), - return on equity (ROE), - price/equity (P/E), - price/sales (P/S)	stock performance: - well - poor
predicting stock performance (Swales and Yoon, 1992, 1996)	Backprop	9	- recurring themes in president's letter to stockholders (qualitative data)	stock performance: - well - poor

NN application	NN algorithm	DATA MODEL		
		No. of input varia-bles	Input variables	Output variables
predicting the stock return (Chenoweth and Obradovic, 1997)	hybrid approach (2 Backprop + expert system)	6 – daily, 8 - monthly data	daily data: - return on 30 year Government bonds, rate change in the return of lagged US Treasury bills, - return on S&P Composite Index - lagged return on S&P Composite Index , monthly data: - return on 30 year Government bonds, lagged rate of change in the return of Government bonds, - US Treasury Bill Index, - lagged rate of US Treasury bills, - the CPI, - the S&P Composite Index.	daily and monthly rate of return (annual rate of return is computed later to measure the performance of the systems)
predicting TOPIX index (Kohara et al., 1997)	Backprop, Recurrent	5	- Tokyo stock exchange price index (close) - dollar-to-yen exchange rate - interest rate - price of crude oil (dollars/barrel) - Dow Jones average	1 – TOPIX prediction for the next day
predicting return volatility on index (Donaldson, Kamstra, 1997)	Backprop	2	- MA variance model prediction - GARCH model prediction	1 – volatility of return on market index
predicting stock implied volatility (Refenes et al., 1997)	Backprop	6	- Moneyness - Change in spot - Maturity effect - Volatility lag1, lag2, lag3	1 – stock implied volatility

NN application	NN algorithm	DATA MODEL		
		No. of input varia-bles	Input variables	Output variables
stock price prediction (Saad et al., 1998)	Time Delay, Recurrent and Probabilistic NN	1 + 6 lags	- today's stock price - lagged stock prices	1 – next day stock price

As illustrated in Table 4, the researchers have used various data models, and no model can be considered as predominant. This variety could cause difficulties in constructing a paradigm of NN efficiency. The number of input variables ranges from 3 (Trippi and DeSieno, 1992) to 88 (Kryzanowski, Galler, and Wright, 1993). 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 (1992, 1996) and Kohara et. al. (1997) have used quantitative data, mostly from the same sources: stock market indexes (S&P, TOPIX, Dow Jones, etc.) or Fortune 500 and Business Week Top 1000 (Yoon et al., 1994). Introducing qualitative data is the new approach to NN applications that opens possibilities for the further research. Improvement is also achieved by Donaldson and Kamstra (1997) by combining NNs and statistical methods in the way that input variables into the NN are the predictions of the MA variance and GARCH model.

3.3. Comparative Analysis on NN Methodology Used in Previous Research

In order to provide the methodological starting point for our experiments, a comparative analysis of NN methodology is conducted in relation to: (a) NN architectures used, (b) optimizing techniques of NN structure and parameters used, (c) evaluation measures and results obtained. There are a few synthetic papers on the review of NN applications in business with the focus on application areas (Li, 1994; Zahedi, 1997; Wong et al., 1997) and the methodology (Zahedi, 1997; Zekic, 1998). They show that no defined paradigm is still developed for using a specific NN methodology in certain problem domains in business, as well as in finance and investing.

According to many authors, NN methodology includes the design of NN architecture (topology), and methods of training, testing, evaluating, and implementing the network (Zahedi, 1993).

NN Architectures Used in Previous Research

The table below shows NN algorithms and structures used in different applications according to the 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 rare applications. The three-layer structure seems to be more effective according to many authors, with the exception of two applications (Schoeneburg, 1990; Refenes et al., 1994) where the four-layer structure outperforms other structures.

Table 5. NN algorithms and structure according to problem domain

Problem domain	NN architecture	
	Algorithm	NN structure
Predicting stock performance (classification)	1. Backprop (Swales and Yoon, 1992, 1996) 2. Backprop (Trippi, DeSieno, 1992) 3. Boltzman machine (Kryzanowski, Galler, and Wright, 1993) 4. Backprop (Yoon et al., 1994) 5. Backprop (Refenes et al., 1997)	1. 2,3, and 4 layers (9-3-3-2)[1] (Swales and Yoon, 1992, 1996) 2. 6 feedforward networks (Trippi and DeSieno, 1992) 3. 2 layers (88-1) (Kryzanowski, Galler, and Wright, 1993) 4. 1 layer (4 inputs, 2 outputs, hidden varying from 0 to 9) 5. 3 layers (6 inputs, 1 output, hidden varying from 2 to 5)

[1] 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 2 neurons. The structure of layers is omitted for the papers in which the authors did not mention it.

Problem domain	NN architecture	
	Algorithm	NN structure
Stock price (or stock returns) predictions	1. Backprop (Grudnitzky and Osburne, 1993) 2. Backprop (Schoeneburg, 1990) 3. Perceptron (Schoeneburg, 1990), 4. ADALINE / MADALINE (Schoeneburg, 1990) 5. Hybrid (2 Backprop NNs + ES) (Chenoweth and Obradovic, 1997) 6. Backprop (Kohara et al., 1997) 7. Recurrent (Kohara et al., 1997) 8. Backprop (Donaldson and Kamstra, 1997) 9. Time Delay, Recurrent, Probabilistic (Saad et al., 1998)	1. 3 layers (24-24-1) (Grudnitzky and Osburne, 1993) 2. 4 layers (10-10-10-1) (Schoeneburg, 1990) 3. 2 layers (40-1) (Schoeneburg, 1990) 4. 2 layers (40-1) (Schoeneburg, 1990) 5. daily data - 3 layers (6-4-1) monthly data – 3 layers (8-31) 6. 3 layers (5-5-1,6-6-1) 7. 3 layers (25-20-1, 26-20-1) 8. 3 layers (2-3-1), optimized 9. 3 layers , min. 7-3-1, max. 10-7-1
Modeling stock performance (ANN combined forecasts)	1. Hybrid approach (Backpropagation NN + expert system) (Yoon, Guimaraes, and Swales, 1994)	1. 3 layers (4-7-2) (Yoon, Guimaraes, and Swales, 1994)

Furthermore, Table 5 also shows that a hybrid approach is used in modeling the stock performance, while individual NN algorithms are used in other problem domains. The exception is the work of Donaldson and Kamstra (1997) who also applied a form of a hybrid approach, but integrating the outputs of statistical methods (MAV and GARCH) as input variables into the NN.

The next characteristic of NN methodology is a transfer function. It is found that the majority of NN 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 an NN system, such as expert systems, genetic algorithms, natural language processing. The number of Kohonen's, Hopfiled's, and other algorithms is relatively small in the stock market NN applications. This could be caused by the convenience of those NN algorithms for classification rather than prediction (Zahedi, 1993), although some researchers suggest the investigation of those and other algorithms on stock market applications as a guideline for further research (Schoeneburg, 1990; Yoon et al., 1994). One step toward investigating other NN algorithms than Backpropagation is the usage of Time-Delayed, Recurrent and Probabilistic networks with great success in false alarm accuracy (Saad et al., 1998).

Optimizing Techniques of NN Structure and Parameters Used in Previous Research

Most of the authors mentioned in Table 5 set the number of hidden neurons in their NNs heuristically. Some of them test only one structure (Grudnitzky and Osburne, 1993), while others test several possible structures by varying the number of hidden neurons and hidden layers (Schoeneburg, 1990; Swales and Yoon, 1992, 1996; Trippi and DeSieno, 1992) by testing all of the combinations with no on-line optimizing procedure for structure. Recent papers apply some of the cross-validation procedures such as Donaldson and Kamstra (1997) who use a standard ten-fold cross-validation selection procedure according to Hjorth and Holmqvist. The procedure is the following:

1) the model is estimated on the portion of in-sample data (training data sample),
2) the estimated model is used to forecast the remaining portion of the in-sample data (test1 data sample),
3) the network is tested on out-of-sample dataset (test2 data sample),
4) a subset of the in-sample data is left out, and a subset of the out-of-sample data is included in,
5) the steps 1 to 4 are repeated until the out-of-sample forecast is produced on the whole initial in-sample set.

Even smaller is the number of researchers that optimize network learning parameters such as learning rate and momentum in Delta rule, and other parameters for other rules. The fact that maybe some of the authors did perform, but did not report their optimizing procedure should also be taken into consideration.

It can be concluded that advanced structure and parameter optimizing techniques have not beed investigated enough in NNs applications on stock market predictions.

Evaluation Measures and Results of Previous Research

Although the authors of previous papers use various evaluation measures (i.e. objective functions) in their networks, accuracy rate is the most frequent one. In most analyzed applications, NN results outperform statistical methods, such as multiple linear regression analysis (Refenes et al., 1994), discriminative analysis (Swales and Yoon, 1992, 1996) and others. The accuracy rate of NN systems ranges from 58% to 90% (Schoeneburg, 1990). Table 6 shows the distribution of NN evaluation metrics and systems' results in analyzed papers.

Table 6. NN evaluation measures and results in analyzed NN applications

NN applications	Evaluation measure (performance criteria)	Results
1. stock performance modeling (Refenes, et al., 1994) 2. prediction of index stock return volatility (Donaldson and Kamstra, 1997)	1. RMS 2. RMSE (root mean squared error) and RMAE (root mean absolute error)	1. RMS of NN=0.066, RMS of regression =0.128 2. RMSE: 0.00135, 0.00117, 0.00124, 0.00067 RMAE: 0.00862, 0.00746, 0.00930, 0.00665
3. stock price prediction (Schoeneburg, 1990) 4. predicting stock performance (Swales and Yoon, 1992,1996) 5. classification of stocks (Kryzanowski, Galler, and Wright, 1993) 6. predicting stock performance (Yoon et al., 1994)	3. accuracy rate 4. accuracy rate 5. accuracy rate 6. accuracy rate	3. 90% for Commerzbank, 80% for BASF, 58% for Mercedes 4. NN 77%, discriminant analysis 65% 5. 72% 6. NN 76%, discriminant analysis 63%
7. predicting implied stock volatility (Refenes et al., 1997)	7. correlation and accuracy rate	7. correlation: NN 0.676, Box-Jenkins 0.50, MLR 0.63, accuracy rate: NN 74%, Box-Jenkins 65.3%, MLR 73.46%
8. predicting TOPIX index (Kohara et al., 1997)	8. trade profit	8. highest profit=40%
9. stock return prediction (Chenoweth, Obradovic, 1997)	9. annual rate of return (Chenoweth, Obradovic, 1997)	9. best result: 13.35% on daily data, 16.39% on monthly data
10. stock price prediction (Saad et al., 1998)	10. % of false alarms	10. best 0%, worst 13.6%

RMS error and its variations (MSE, MAE) are the next most frequently used objective functions (Refenes et al., 1994), which can be explained by the simplicity of observing them. Many authors suggest the usage of other metrics that are more appropriate for stock predictions, such as rate of return, total return, average return, or profit. Recent papers (Chenoweth and Obradovic, 1996; Refenes et al., 1997; Saad et al., 1998) use metrics other than accuracy such as the annual rate of return or correlation. Saad et al. (1998) also use a form of accuracy percentage, but only of the false alarms in order to minimize the false alarms on the market. The accuracy mostly ranges from 70% to 80%. Although the risk for using NNs is still relatively high, NNs outperform statistical methods for 5 - 20% higher accuracy in rate (Refenes et al., 1994; Swales and Yoon, 1992). 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. Results of the hybrid approaches are very promising. Donaldson and Kamstra (1997) obtained very low RMS and MAE using the outputs of the statistical methods as the inputs into the NN. In comparison to the individual statistical methods tested (MAV and GARCH) NNs outperform significantly. It is also shown that NNs slightly, but not significantly outperform Box-Jenkins and multiple regression in stock volatility forecast (Refenes et al., 1997).

However, researchers who combined NNs with expert systems did not mention the percentage of NN correctness (Yoon et al., 1994). 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 (Yoon et al., 1994).

3.4. Benefits, Limitations and Conclusion on Previous Research

Benefits

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

It can be seen from the comparative analysis that the Backpropagation algorithm has the ability to predict with greater accuracy than other NN algorithms in most, but not all cases. Recurrent NN outperforms Backpropagation in the paper which has tested both architectures (Donaldson and Kamstra, 1997). 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 some data are not available. It has been proven that NN outperforms classical forecasting and statistical methods, such as multiple regression analysis (Trippi and DeSieno, 1992, Refenes et al., 1997) 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. The analysis also shows great possibilities of NN methodology in various combinations with other methods, such as expert systems. The combination of the NN's calculating ability 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.

Limitations

Some of the limitations of NNs detected in the previous research on NN applications on stock markets are: (1) NNs require very large number of previous cases (Yoon et al., 1994); (2) "the best" network architecture (topology) is still unknown (Schoeneburg, 1990); (3) for more complicated networks, reliability of results may decrease (Yoon et al., 1994); (4) statistical relevance of the results is needed (Schoeneburg, 1990); and (5) a more careful data design is needed (Refenes et al., 1994). 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 (Schoeneburg, 1990). The limitation still exists for the problems that do not have much of the 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. In order to overcome the third limitation, concerning the reliability of results, further experiments on testing various network architectures are required. The problem with evaluating NN reliability is connected with the next limitation, the need for more determined 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.

Conclusion on Previous Research

It can be concluded from the previous research that: (1) NNs are efficient 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 a very promising problem domain of NN applications; (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) NN structure on stock market application is very rarely optimized using the advanced techniques such as pruning, cascading, and others, (5) accuracy rate is the most frequent evaluation measure although stock return and profit are suggested, (6) benefits of NN are in their ability to predict accurately even in situations with uncertain data, and in possible combinations with other methods; (7) limitations have to do with insufficient reliability tests, data design, and the inability to identify the optimal topology for a certain problem domain.

Many 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 (Grudnitzky and Osburne, 1993). Additionally, future research should focus on the examinations of other types of networks that were rarely applied, such as Hopfiled'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.

Zahedi (1997) emphasizes some issues in NN applications that should be investigated more:

1) In the financial applications:

a) open issues regarding input data:

- to analyze the sample size and its impact to NN efficiency,
- to analyze time interval and sensitivity of results to time interval (is dividing the sample data into various sets one of the solutions?),
- to analyze the distribution of various categories of output data,
- to filter data by more statistical transformations,
- to determine the appropriate number of input variables or to select input variables (is one of the solutions deleting variables with low weights in NN?),
- to use statistics (correlation and regression) in order to identify the variables that are most important in the outcome,
- to use more qualitative data.

b) open issues regarding underlying structure of data:

- to have a balanced data set,
- to investigate which methods are better for the data with inherent nonlinearity and which for the linear data,
- more investigation about the underlying structure of data is needed,

c) open issues regarding NN structure:

- to identify circumstances for a certain type of architecture and to test more architectures, not only Backpropagation (more systematic reporting of architecture and parameter selection),
- to deal more with the problem of local minima in Backpropagation,
- to guide multi-NN development (theoretical and practical experiments),
- to identify testable metrics for the suitability of one structure over another,

d) open issues regarding performance metrics:

- the need for the test that could establish the significance of MAPE and % of correct and incorrect categorization,
- to check the assumptions given for the R^2,
- to use more comparisons of financial rates, such as rate of return, rate of profit, etc.
- if using the comparison of the profit return with the market average, we need to be certain that the metrics include all relevant information (compatibility of risk levels, transaction costs, etc.),

- to establish standard metrics with features of testability and comparability,
- to use statistical analysis to discover the strength and weaknesses of the system,
- to develop the metrics that test the robustness of the system with respect to new patterns (measuring and analyzing the system robustness),

2) In comparative studies of NN and statistical methods:

- to develop methods and innovative approaches to study the underlying data structure before the application,
- to develop and investigate different ways to make predictions, such as bootstrapping, and on-line learning.

We address some of these issues in our experiments (see Chapter 4) such as preprocessing of input data, testing an appropriate number of input variables using forward selection strategy in the Factoral model, investigation which methods are better for different underlying structures of data. We also identify circumstances for the usage of certain types of architecture and test more architectures, not only Backpropagation, then we use advanced optimizing techniques for structure and parameters optimization, simulated annealing in order to prevent local minima, and testable performance metric that is suitable for the problem and comparable across the methods and models.