



# Improving returns on stock investment through neural network selection

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## Abstract

The Artificial Neural Network (ANN) is a technique that is heavily researched and used in applications for engineering and scientific fields for various purposes ranging from control systems to artificial intelligence. Its generalization powers have not only received admiration from the engineering and scientific fields, but in recent years, the finance researchers and practitioners are taking an interest in the application of ANN. Bankruptcy prediction, debt-risk assessment and security market applications are the three areas that are heavily researched in the finance arena. The results, this far, have been encouraging as ANN displays better generalization power as compared to conventional statistical tools or benchmark.

With such intensive research and proven ability of the ANN in the area of security market application and the growing importance of the role of equity securities in Singapore, it has motivated the conceptual development of this project in using the ANN in stock selection. With its proven generalization ability, the ANN is able to infer from historical patterns the characteristics of performing stocks. The performance of stocks is reflective of their profitability and the quality of management of the underlying company. Such information is reflected in financial and technical variables. As such, the ANN is used as a tool to uncover the intricate relationships between the performance of stocks and the related financial and technical variables. Historical data such as financial variables (inputs) and performance of the stock (output) are used in this ANN application. Experimental results obtained this far have been very encouraging. © 1999 Elsevier Science Ltd. All rights reserved.

**Keywords:** Technical analysis; Fundamental analysis; Neural network; Economic factors; Political factors; Firm specific factors

## 1. Introduction

With the growing importance in the role of equities to both the international and local investors, the selection of attractive stocks is of utmost importance to ensure a good return. Therefore, a reliable tool in the selection process can be of great assistance to these investors. An effective and efficient tool/system gives the investor the competitive edge over others as he/she can identify the performing stocks with minimum effort.

Trading strategies, rules and concepts based on fundamental and technical analysis, have been devised by both academics and practitioners in assisting the investors in their decision making process. Innovative investors opt to employ information technology to improve the efficiency in the process. This is done through transforming trading strategies into computer known languages so as to exploit the logical processing power of the computer. This greatly reduces the time and effort in short-listing the list of attractive stocks.

In this age where information technology is dominant, such computerized rule based expert systems have great limitations that will affect its effectiveness and efficiency. However, with the significant advancement in the field of Artificial Neural Network (ANN), these limitations have found a solution. In this research, the generalization ability of the ANN is being harnessed in creating an effective and efficient tool for stock selection. Results of the researches in this field have so far been very encouraging.

## 2. Application of neural network in financial and commercial domains

Research developments in Bankruptcy prediction have showed that the ANN performs better than the conventional statistical methods such as Discriminant Analysis and Logistic Regression. Alici (1996), using UK data, shows that ANN, with the architecture consisting of 3 multi layer Preceptron (28 financial inputs, seven hidden neurons and two output neurons) has an average of 71.38%(76.07%) for the failed firms (healthy firms) using neural network. On the other hand, the Discriminant Analysis and Logistic Regression have both achieved 60.12%(71.43%) and

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65.29%(71.07%) for the failed firms (Healthy Firms). The feasibility of applying ANN into bankruptcy was also studied by Raghupathi, Schkade and Raju (1991), Odom and Sharda (1993), and many others.

Salchenberger, Cinar and Lash (1992) use the ANN for classifying failure pertaining to the Savings and Loans (S&Ls) organizations in US. In the Debt Risk Assessment applications, Dutta and Shekhar (1993) use neural network to classify bonds.

The generalization ability of the ANN is also extended to commodity trading (copper). Robles and Naylor (1996) are able to show that the ANN outperforms the traditional Weighted Moving Average rule and a “buy and hold” strategy. In equity, Gencay and Stengos (1996) show that the ANN outperforms the GARCH (linear model) in the identical research methodology. The ratios of the average MSPE of the testing model and benchmark are 0.961 and 1 for the ANN and the GARCH, respectively.

Burgess and Refenes (1996) prove that, the ANN has better generalization ability than Ordinary Least Square in predicting daily return of the FTSE index. Neural network is also applied in predicting the trend of Italian stock market (COMIT). Chinetti and Rossignoli (1993) attempted to use technical variables to build an accurate prediction system to forecast the timing of buying and selling for the COMIT index. Westheider (1994) studied the predictive power of the ANN on stock index returns. He uses economic and fundamental variables to predict monthly, quarterly and yearly returns.

### 3. Neural architecture

The computer software selected for the training and testing the network is Neural Planner version 3.71. This software was programmed by Stephen Wolstenholme. It is an ANN simulator strictly designed for only one Back Propagation learning algorithm.

There are four major issues in the selection of the appropriate network:

1. Select the Appropriate Algorithm.
2. Architecture of the ANN.
3. Selection of the Learning Rule.
4. Selection of the Appropriate Learning Rates and Momentum.

#### 3.1. Select the Appropriate Algorithm

Since the sole purpose of this project is to identify the top performing stocks and the historical data that are used for the training process will have a known outcome (whether it is considered Top performer or otherwise), algorithms designed for supervised learning are ideal. Among the available algorithms, the Back Propagation algorithm designed by Rumelhart, Hinton and Williams (1986) is the most suitable as it is being intensively tested in Finance. Moreover, it

is recognized as a good algorithm for generalization purposes.

#### 3.2. Architecture of ANN

Architecture, in this context, refers to the entire structural design of the ANN (Input Layer, Hidden Layer and Output Layer). It involves determining the appropriate number of neurons required for each layer and also the appropriate number of layers within the Hidden Layer. The logic of the Back Propagation method is the Hidden Layer. The Hidden Layer can be considered as the crux of the Back Propagation method. This is because hidden layer can extract higher level features and facilitate generalization, if the input vectors have low level features of a problem domain or if the output/input relationship is complex. The fewer the hidden units, the better is the ANN able to generalize. It is important not to over-fit the ANN with large number of hidden units than required until it can memorize the data. This is because the nature of the hidden units is like a storage device. It learns noise present in the training set, as well as the key structures. No generalization ability can be expected in these. This is undesirable as it does not have much explanatory power in a different situation/environment.

#### 3.3. Selection of the Learning Rule

The learning rule is the rule that the network will follow in its error reducing process. This is to facilitate the derivation of the relationships between the input(s) and output(s). The generalized delta rule developed by Rumelhart et al. (1986) is used in the calculations of weights. This particular rule is selected because it is heavily used and proven effective in the Finance researches.

#### 3.4. Selection of the Appropriate Learning Rates and Momentum

The Learning Rates and Momentum are parameters in the learning rule that aid the convergence of error, so as to arrive at the appropriate weights that are representative of the existing relationships between the input(s) and the output(s).

As for the appropriate learning rate and momentum to use, the NEURAL PLANNER Software has a feature that can determine appropriate learning rate and momentum for the network to start training with. This function is known as “Smart Start”. Once this function is activated, the network will be tested using different values of learning rates and momentum to find a combination that yields the lowest average error after a single learning cycle. These are the optimum starting values as using these rates improve error converging process, thus require less processing time.

Another attractive feature is that the software comes with an “Auto Decay” function that can be enabled or disabled. This function automatically adjusts the learning rates and

momentum to enable a faster and more accurate convergence. In this function, the software will sample the average error periodically, and if it is higher than the previous sample then the learning rate is reduced by 1%. The momentum is “decayed” using the same method but the sampling rate is half of that used for the learning rate. If both the learning rate and momentum decay are enabled then the momentum will decay slower than the learning rate.

In general cases, where these features are not available, a high learning rate and momentum (e.g. 0.9 for both the Learning Rates and Momentum) are recommended as the network will converge at a faster rate than when lower figures are used. However, too high a Learning Rate and Momentum will cause the error to oscillate and thus prevent the converging process. Therefore, the choice of learning rate and momentum are dependent on the structure of the data and the objective of using the ANN.

#### 4. Variables selection

In general, financial variables chosen are constrained by data availability. They are chosen first on the significant influences over stock returns based on past literature searches and practitioners’ opinions and then on the availability of such data. Most of the data used in this research is provided by Credit Lyonnais Securities (Singapore) Pte Ltd. Stock prices are extracted from a financial database called INVESTAMATIC.

Broadly, factors that can affect stock prices can be classified into three categories: economic factors, political factors and firm/stock specific factors. Economic factors have significant influence on the returns of individual stock as well as stock index in general as they possess significant impact on the growth and earnings’ prospects of the underlying companies thus affecting the valuation and returns. Moreover, economic variables also have significant influence on the liquidity of the stock market. Some of the economic variables used are: inflation rates, employment figures and producers’ price index.

Many researchers have found that it is difficult to account for more than one third of the monthly variations in individual stock returns on the basis of systematic economic influences, and shown that political factors could help to explain some of the missing variations. Political stability is vital to the existence of business activities and the main driving force in building a strong and stable economy. Therefore, it is only natural that political factors such as fiscal policies, budget surplus/deficit etc do have effects on stock price movements.

Firm specific factors affect only individual stock return. For example, financial ratios and some technical information that affects the return structure of specific stocks, such as yield factors, growth factors, momentum factors, risk factors and liquidity factors. As far as stock selection is concerned, firm specific factors constitute to important

considerations as it is these factors that determine whether a firm is a bright start or a dim light in the industry. Such firm specific factors can be classified into five major categories:

1. Yield factors: these include “historical P/E ratio” and “Prospective P/E ratio”. The former is computed by price/earning per share. The latter is derived by price/consensus earnings per share estimate. Another variable is the “cashflow yield”, which is basically price/operating cashflow of the latest 12 months.
2. Liquidity factors: the most important variable is the “market capitalization”, which is determined by “price of share  $\times$  number of shares outstanding”.
3. Risk factors: the representative variable is the “earning per share uncertainty”, which is defined as “percentage deviation about the median EPS estimates”.
4. Growth factors: basically, this means the “return on equity (ROE)”, and is computed by “net profit after tax before extraordinary items/shareholders equity”.
5. Momentum factors: a proxy is derived by “average of the price appreciation over the quarter with half of its weights on the last month and remaining weights being distributed equally in the remaining two months”.

The inputs of the neural network stock selection system are the above seven inputs and the output is the return differences between the stock and the market return (excess returns). This is to enable the neural network to establish the relationships between inputs and the output (excess returns).

The training data set will include all data available until the quarter before the testing quarter. This is to ensure that the latest changes in the relationship of the inputs and the output are being captured in the training process.

#### 5. Experiment

The quarterly data required by the project are generally stock prices and financial variables (inputs to the ANN stock selection system) from 1/1/93 to 31/12/96.

Stock Prices, which are used to calculate stock returns, are extracted from the Financial Database called INVESTAMATIC. These stock returns, adjusted for dividends, stock splits and bonus issues, will be used as output in the ANN training process.

One unique feature of this research is that Prospective P/E ratio, measured as (Price/Consensus Earnings Per Share Estimate), is being used as a forecasting variable. This variable has not received much attention in Financial Research. Prospective P/E ratio is used among practitioners as it can reflect the perceived value of stock with respect to EPS (Earnings per share) expectations. It is used as a value indicator, which has similar implications as that of the Historical P/E ratio. As such, a low Prospective P/E suggests that the stock is undervalued with respect to its future earnings

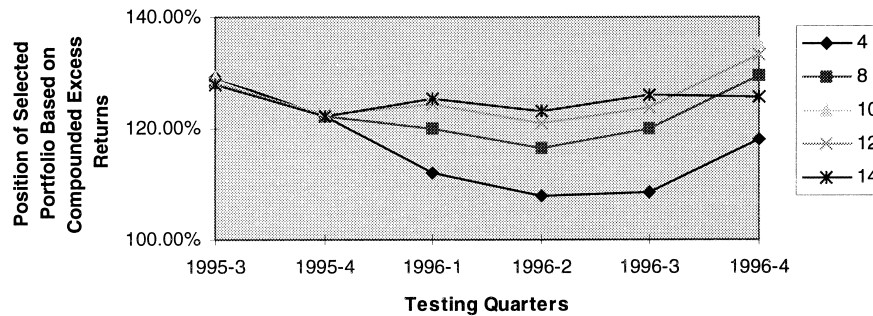


Fig. 1. Graphical presentation of excess returns for 15 000 cycles.

and vice versa. With its explanatory power, Prospective P/E ratio qualifies as an input in the stock selection system. Data on Earnings per Share estimates, which is used for the calculation of EPS Uncertainty and Prospective P/E ratio, is available in THE ESTIMATES DIRECTORY. This is a compilation on EPS estimates and recommendations are put forward by financial analysts. The coverage has estimates from countries over the Asia Pacific Rim as from January 1993.

### 5.1. Research design

The purpose of this ANN stock selection system is to select stocks that are top performers from the market (Stock that outperformed the market by 5%) and to avoid selecting under performers (Stocks that underperformed the market by 5%). More importantly, the aim is to beat the market benchmark (Quarterly return on the SESALL index) on a portfolio basis.

This ANN stock selection system is a quarterly portfolio re-balancing strategy whereby it will select stocks in the beginning of the quarter and performance (the return of the portfolio) will be assessed at the end of the quarter.

### 5.2. Design 1 (Basic System)

In this research design, the sample used for training consists of stocks that outperformed and underperformed the market quarterly by 5% from 1/1/93 to 30/6/95.

The inputs of the ANN stock selection system are the seven inputs chosen in Section 4 and the output will be the return differences between the stock and the market return (excess returns). This is to enable the ANN to establish the relationships between inputs and the output (excess returns).

The training data set will include *all data available until the quarter before the testing quarter*. This is to ensure that the latest changes in the relationship of the inputs and the output are being captured in the training process.

The generalization ability of the ANN in selecting top performing stocks and whether the system can perform is tested across time. The data used for the selection process are from the third quarter of 1995 (1/7/95–30/9/95), the fourth quarter of 1995 (1/10/95–31/12/95), the first quarter of 1996 (1/1/1996–31/3/1996), the second quarter of 1996

(1/4/1996–30/6/1996), the third quarter of 1996 (1/7/1996–30/9/1996), the fourth quarter of 1996 (1/10/1996–31/12/1996). The limited test duration is constrained by the data availability.

The testing inputs are being injected into the system and the predicted output will be calculated using the established weights. After which, the top 25 stocks with the highest output value will be selected to form a portfolio of stocks. These 25 stocks are the top 25 stocks recommended for purchase at the beginning of the quarter. Generalization ability of the ANN will be determined by the performance of the portfolio, measured by excess returns over the market as well as the % of top performers in the portfolio as compared to the benchmark portfolio (Testing Portfolio) at the end of the month.

### 5.3. Design 2 (Moving Window System)

The Basic System is constrained by meeting the minimum sample size required for training process. However, this second design is going to forgo the recommended minimum sample size and introduce a Moving Window concept. This is to analyze the ANN ability to perform under a restricted sample size environment.

The inputs and output variables are identical with that of the Basic System, but the training and testing samples are different. The Moving Window System uses three quarters as training sample and the subsequent quarter as the testing sample. The selection criterion is also identical with that of the Basic System in research Design 1.

### 5.4. Results

The ANN is made to train with 10 000 and 15 000 cycles. The reason for using these numbers of cycles for training is because the error converging is generally slow after 10 000 thus suggesting adequate training. Moreover, it does not converge beyond 15 000. This is an indicator that the network is over-trained.

The training of four hidden neurons for 10 000 cycles takes approximately 1.5 h, eight hidden neurons takes about 3 h and the most complex (14 hidden neurons) took about 6 h on a Pentium 100 MHz PC. As for those architectures that require 15 000 cycles, it usually takes

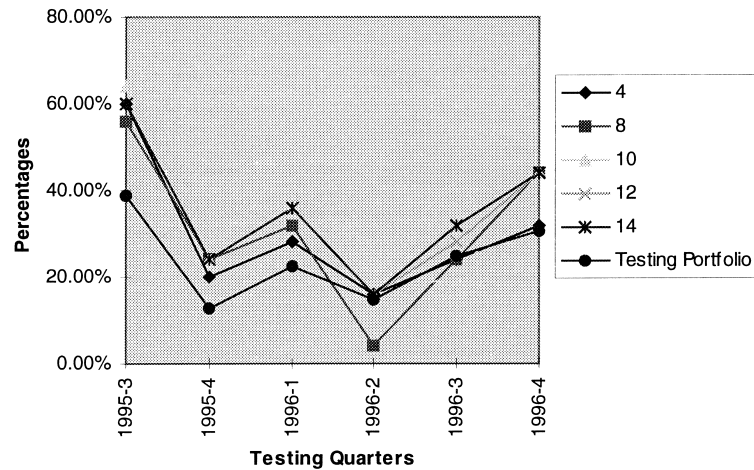


Fig. 2. Performance of portfolios with % of stocks with actual return of 5% above market for 10 000 cycles.

about 1.5 times the time it takes to train the network for 10 000 cycles.

The results of the Basic Stock Selection System based on the training and testing schedules mentioned are presented in two forms: (1) the excess return format and (2) the percentage of the top performers in the selected portfolio. These two techniques will be used to assess the performance and generalization ability of ANN.

Testing results show that the ANN is able to “beat” the market overtime, as shown by positive compounded excess returns achieved consistently throughout all architectures and training cycles. This implies that the ANN can generalize relationships overtime. Even at individual quarters’ level, the relationships between the inputs and the output established by the training process is proven successful by “beating” the market in 6 out of 8 possible quarters which is a reasonable 75%. (Fig. 1.)

The Basic Stock System has consistently performed better than the testing portfolio overtime. This is evident by the fact that the selected portfolios have higher percentage of top performing stocks (above 5%) than the testing

portfolio overtime. This ability has also enabled the network to better the performance of the market (SESALL index) presented earlier. (Figs. 2 and 3.)

The Moving Window Selection System is designed to test the generalization power of the ANN in an environment with limited data.

The generalization ability of the ANN is again evident in the Moving Window Stock Selection System as it outperformed the Testing portfolio in 9 out of 13 testing quarters (69.23%). This can be seen in the graphical presentation that the line representing the selected portfolio is above the line representing testing portfolio most of the time. (Fig. 4.) Moreover, the compounded excess returns and the annualized compounded excess returns are better than that of the testing portfolio by two times over. The selected portfolios have outperformed the market 10 out of 13 (76.92%) testing quarters and excess returns (127.48% for the 13 quarters and 36.5% for the Annualized compounded return), which proved its consistent performance over the market (SESALL index) overtime. (Fig. 5.)

The Selected Portfolios have outperformed the Testing

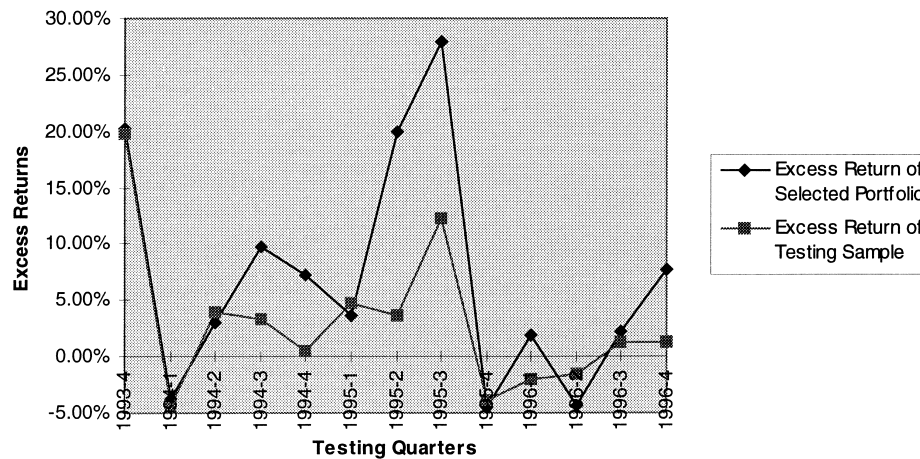


Fig. 3. Graphical presentation of excess returns of portfolio.

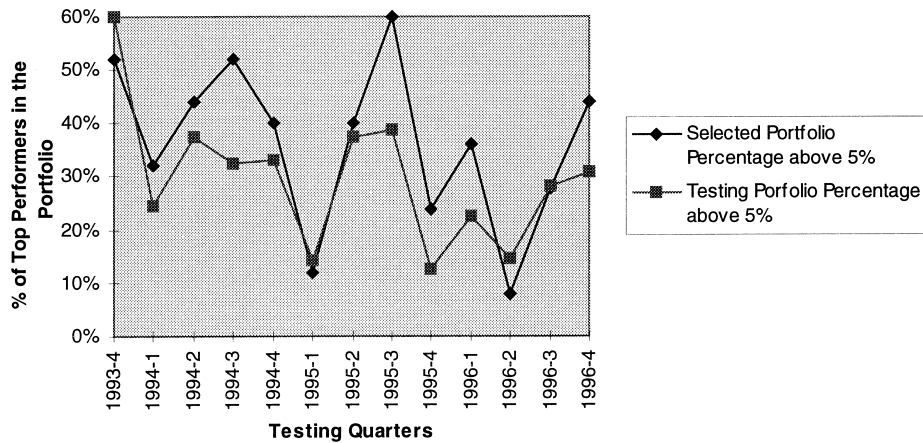


Fig. 4. % of Top performers in the portfolio - moving window stock selection system.

Portfolio in nine (69.23%) and equal the performance in one occasion. This further proves the generalization ability of the ANN. Moreover, the ability to avoid selecting undesirable stocks is also evident by the fact that the selected portfolios have less of this kind of stocks than the testing portfolio in 10 out of 13 occasions (76.92%).

From the experimental results, the portfolio of the Selected portfolios outperformed the Testing and Market portfolios in terms of compounded actual returns overtime. The reason is because the Selected portfolios outperform the two categories of portfolios in most of the testing quarters thus achieving better overall position at the end of the testing period.

## 6. Conclusion and future works

The ANN has displayed its generalization ability in this

particular application. This is evident through the ability to single out performing stock counters and having excess returns in the Basic Stock Selection System overtime. Moreover, neural network has also showed its ability in deriving relationships in a constrained environment in the Moving Window Stock Selection System thus making it even more attractive for applications in the field of Finance.

This paper is largely constrained by the availability of data. Therefore, when more data is available, performance of the neural networks can be better assessed in the various kinds of market conditions, such as bull, bear, high inflation, low inflation or even political conditions in which all have different impact on stocks.

Also, as more powerful neural architectures are being discovered by researchers on a fast pace, it is good to repeat the experiments using several architectures and compare the results. The best performance structure may than be employed.

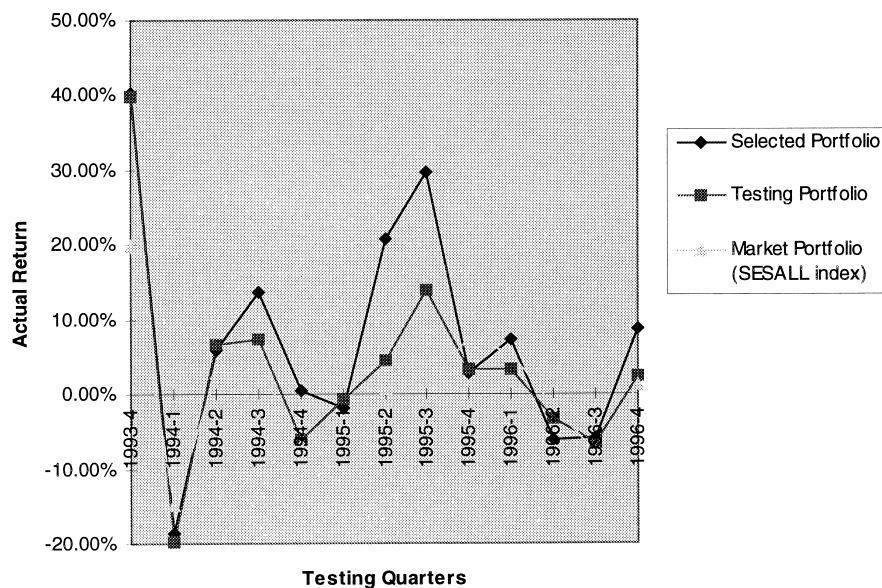


Fig. 5. Actual returns - moving window stock selection system.

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