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*Published in:*

Proceedings of the 10th IASTED International Conference on Artificial Intelligence and Soft Computing, ASC 2006

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*Recommended citation(APA):*

Vanstone, B., & Finnie, G. (2006). Combining technical analysis and neural networks in the Australian stockmarket. In A. P. del Pobil (Ed.), *Proceedings of the 10th IASTED International Conference on Artificial Intelligence and Soft Computing, ASC 2006* (pp. 125-130)  
<http://www.actapress.com/Abstract.aspx?paperId=28168>

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August 2006

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## Recommended Citation

Bruce Vanstone and Gavin Finnie. (2006) "Combining Technical Analysis and Neural Networks in the Australian Stockmarket". Aug. 2006.

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# COMBINING TECHNICAL ANALYSIS AND NEURAL NETWORKS IN THE AUSTRALIAN STOCKMARKET

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## ABSTRACT

One of the greatest difficulties facing a stock trader or investment manager is the stock selection process. In this process, the investor is faced with a large number of competing investments, and a fixed amount of capital. The goal is to spread the available capital across a reduced subset of the competing investments, with the aim of increasing the return. Typically, the investor relies on one of two main frameworks to guide the selection process, namely Fundamental Analysis, and Technical Analysis. This paper focuses on Technical Analysis, and implements a neural network which supports the stock selection process.

## KEY WORDS

Stockmarket, Trading, Neural Networks

## 1. Introduction

As stated above, there are two main models in common usage which forms the basis of most traders' decisions. These are Fundamental Analysis and Technical Analysis.

Fundamental Analysis involves a detailed study of a company's financial position, and is often used to provide general support for price predictions over a long term. Typically, traders using this approach have long-term investment horizons, and access to the type of data published in most company's financial reports. Fundamental analysis provides mechanisms to scrutinize a company's financial health, often in the form of financial ratios. These ratios can be compared with other companies in similar environments. Further information concerning combining Fundamental Analysis with Neural Networks can be found in the authors previous paper, see Vanstone et al [1].

Technical Analysis provides a framework for studying investor behaviour, and generally focuses on price and volume data, along with derivatives of this data, principally indicators and oscillators. Typically, traders using this type of approach concern themselves chiefly with timing, and are generally unaware (or uninterested) in a company's long-term financial health. Traders using this approach usually have short term investment horizons, and access to price and exchange data.

Regardless of the decision model in use, there are a variety of common issues. One important issue, the subject of this paper, is the issue of security selection. Essentially, there are a great many tradeable securities in the market, and a trader has a limited amount of capital. Common to all investors is the desire to maximize returns. Security selection is the process that a trader uses to determine which securities are likely to have the best chances of capital appreciation, and therefore, represent the best investments.

This paper focuses on the technical model, and studies the variables which technical analysts use to make the selection process. It briefly describes the characteristics of these processes, their origins and credibility, and then moves on to the enhancement of these processes using artificial neural networks.

This paper will not focus specifically on technical investment procedures. Rather, it will analyze research related to using technical data for security selection, with the aim of determining key technical variables in use. It will review the literature to date, highlighting the technical variables believed to be important within the literature. The paper will then develop neural network models from the combined technical variables involved, and assess their effectiveness as security selectors.

## 2. Review of Literature

Modern Technical Analysis dates from the work of Charles Dow, who in 1884 drew up an average of the daily closing prices of 11 important stocks. Between 1900 and 1902, Dow wrote a series of articles in the Wall Street Journal documenting stock price patterns and movements he observed in the average. These articles were the first to describe systematic phenomena in the stock markets.

Although Dow's work represents the beginning of modern technical analysis, it is worthy of note that markets and analysis techniques existed centuries before this, notably in Japan since 1730, where the first futures contracts (in rice) were traded. Tvede [2] reports that interest in the future prices of the 'futures' ran high, with the Japanese government suspending the forward market in 1869 due to excessive volatility.

Today, a manual of technical analysis is likely to be composed of techniques which fall into one of three primary classifications, namely:

- Charting (typically pattern matching),
- Indicators (and oscillators),
- Esoteric approaches

This paper will focus on the technical indicators and oscillators, as these are easily reproduced according to their mathematical definitions. In contrast, Charting and pattern matching is usually highly subjective and without rigorous mathematical definition. Esoteric approaches are excluded from this study, as they have no scientific justification. Warnecke [3] provides examples of the criticisms often leveled at these techniques.

Technical Analysis is enjoying a recent resurgence in academia after having been out of favour for several decades. The main reason for this lack of favour concerns the Efficient Market Hypothesis (EMH), which supports the random-walk theory. In essence, since the early work of Fama [4], the random-walk theory has held sway. This theory states that successive price changes in stock prices are independent, identically distributed random variables. The important implication of this hypothesis is that it implies that a series of price changes has no memory, which further implies that the study of past prices cannot provide a useful contribution to predicting future prices. As the majority of technical analysis focuses on forecasts based on past price behavior, the natural conclusion is that Technical Analysis cannot work.

Regardless of this theory, a large number of market participants continue to use technical analysis as their main method of stock selection. Indeed, Taylor and Allen [5] conducted a UK survey of forex dealers on behalf of the Bank of England, and found that at least 90% of the respondents placed some weight on Technical Analysis

for decision making. It has been suggested that due to its high usage, technical analysis may, in fact, be becoming a self-fulfilling methodology. In other words, if enough people follow the principles, then those principles can be expected to become manifest in the character of price time series.

To complete the discussion regarding technical analysis, it is occasionally stated that as technical rules become more widely known, the abnormal returns they attempt to identify will be reduced, and the usefulness of the technical rule itself will be destroyed. Silber [6] finds against this conclusion, instead concluding that 'the continued success of simple technical trading rules is possible as long as there are price smoothing participants in the market'. In this context, Silber's example of price smoothing participants refers to the central banks.

Rather than focus on Technical Analysis as a discipline, the remainder of this literature review will focus on the research support for the use of Technical Analysis variables, such as Moving Averages, Indicators and Oscillators.

The majority of the academic literature concerning technical analysis concerns the testing of moving average rules. According to Pring [7], there are three basic principles of Technical Analysis, namely:

- Prices move in trends,
- Volume goes with the trend,
- A trend, once established tends to persist

The moving average and its derivatives are designed to expose when a security has begun trending, and as such, deal with the first and third principles listed above. The idea of observing (and profiting from) trends has a long history, and is one of the early systematic phenomena described by Dow.

Academic research in the area of moving averages dates from the work of Neftci and Policano [8], who studied moving averages, and the slope of price movements on the chart (named trendlines by technical analysts). They studied closing prices of gold and T-bills, and created buy-and-sell rules based on trendlines and moving averages. Although they described their results from the study of trendlines as inconclusive, they reported a significant relationship between moving average signals and prices. Of particular interest was the fact that a set of significant parameters for one commodity were often insignificant for another commodity. This difference in significant parameters is often termed a markets 'personality'.

In 1988, Murphy [9] demonstrated that different sectors of the market move in relationships with other sectors, a field of study now known as Intermarket Analysis.

In 1991, Neftci [10] examined the relationship of the 150 day moving average rule to the Dow-Jones Index. This

research concluded that the moving average rule generated Markov times (no dependence on future information) and has predictive value.

Two popular technical trading rules were tested by Brock et al. [11], namely, moving averages and trading range breaks (known by technical analysts as Support and Resistance trading). Using data from the start of the DJIA in 1897 to the last trading day of 1986, the authors test a variety of combinations of moving averages, using a 1% band around predictions to eliminate whipsaws. They find support for the use of moving averages, and report that the differences in utility are not readily explained by risk. They conclude their results are consistent with the technical rules having predictive power.

Inspired by Brock et al [11] above, Mills [12] tests the same two trading rules in the London Stock Exchange, using FT30 data from 1935 – 1994. Mills’s results are remarkably similar to Brocks, with Mills concluding that the trading rules could predict stock prices, and are thus profitable in periods when the market is inefficient.

Levich and Thomas [13] test currency futures contracts in five currencies over the period 1976 to 1990. They report persistent trading profits over the 15 year period using a variety of commonly researched moving average rules. Levich and Thomas concluded ‘the profitability of trend following rules strongly suggest some form of serial dependency in the data, but the nature of the dependency remains unclear’.

LeBaron [14] provided more support for the moving average in 1997, by using moving average rules as specification tests for foreign exchange rates. He concluded that exchange rates do not follow the random walk, and that the deviations are detected by simple moving average rules.

Lehmann [15] considers evidence supporting variation in equity returns, attempting to decide whether the evidence is indicative of predictable changes in expected return, or market inefficiency. Lehmann finds that ‘winners’ and ‘losers’ one week often experience reversals of fortune in the following week. The costless portfolio constructed by Lehmann (difference between ‘winner’ and ‘loser’ portfolios) showed profit in 90% of weeks. Lehmann concludes that the reversals of fortune are probably reflections of the imbalances in the market for short-term liquidity, and states that ‘it is difficult to account for these results within the efficient markets framework’. Lehmann’s work is often quoted by practitioners as supporting Technical Analysis, as it supports the idea that price trends occur frequently enough to create profit opportunities for technical traders. Lehmann does not specifically make this statement.

Jegadeesh [16] examines the predictability of monthly returns on individual securities. Ten portfolios were formed based on the predicted returns using estimates of the regression parameters. The difference between

abnormal returns on the extreme decile portfolios was 2.49 percent per month over the period 1934 to 1987. Slightly different values are provided when comparing extreme decile portfolios excluding January results (2.20% per month), and when January was considered separately (4.37% per month). Jegadeesh rejects the random walk hypothesis, and concludes that returns predictability is due to either market inefficiency, or systematic changes in expected stock returns. This paper is often used to support the principles of technical analysts, as it shows evidence that increases (and decreases) in prices during one month are often reversed out the following month. Patterns of that nature would suggest that investors could profit from technical trading strategies, and would also be a breach of market efficiency.

Very little academic research exists supporting the use of specific technical indicators and oscillators. The main academic work above relates to Moving Average rules and Momentum based rules. To allow the neural network to have access to the same types of indicators and oscillators being used by practitioners, a survey of the main practitioners journal, ‘The Technical Analysis of Stocks and Commodities’ was conducted. For the sake of brevity, detailed reviews are not provided for the articles studied, rather, a list of the most ‘popular’ (i.e. most frequently referenced) technical variables is provided in Table 1. The assumption is that these variables are most in use due to the fact that they are useful.

<b>Technical Variables most frequently cited in ‘The Technical Analysis of Stocks and Commodities’</b>
Moving Averages (including a variety of derivatives built from basic moving averages)
Volatility based variables, such as ATR (Average True Range)
Volume based variables, such as Volume directly, or OBV (On Balance Volume)
ADX (Average Directional Index – See Wilder [17])
Stochastics (based on the work of George Lane)
Momentum (both price and volume)
RSI (Relative Strength Index – See Wilder [17])
Variety of miscellaneous indicators and oscillators (eg MACD, Intermarket indicators, Money Flow, TRIN (Traders Index), etc)

**Table 1 Frequently Cited Technical Variables**

To sum up the position regarding technical analysis, it is reasonable to state that after a long absence from academia, technical analysis is beginning to enjoy a return to mainstream investment finance. It is becoming more common to see universities promote subjects with titles

such as ‘Computational Finance’, and even Siegel [18] ‘cautiously’ supports the use of Moving Averages.

### 3. Methodology

The neural networks built in this study were designed to produce an output signal, whose strength was proportional to expected returns in a 3 day timeframe. In essence, the stronger the signal from the neural network, the greater the expectation of return. Signal strength was normalized between 0 and 100.

An objective measure of a technical short term trading system is its measure of expectancy. The idea of expectancy in trading was first raised by Tharp [19], who proposed it as a useful method to compare trading systems. Expectancy is a measure of the expected profit per dollar risked on a fixed position size basis. It is used without money management settings enabled, which is appropriate for in-sample tests. There are a number of variant formulas for calculating expectancy, this version presented is more conservative than Tharp’s; it uses the average loss as the standard of risk (rather than the minimum loss as used by Tharp).

$$EXPECTANCY = \frac{((AW \times PW) + (AL \times PL))}{|AL|}$$

where

AW = Average amount won on profitable trade

PW = Probability of winning

AL = Average amount lost on losing trade (-ve)

PL = Probability of losing

#### Equation 1 Expectancy

Secondly, to assess the quality of the ANN architecture chosen, it is also appropriate to consider the ‘Average Profit/Loss %’ over the 3 day time period.

This paper uses 10 years of data for the entire Australian stockmarket from the first day of trading in 1994, through to the last day of trading in 2003. The data used includes delisted shares, so as to avoid survivorship bias in the results. Data for this study was sourced from Norgate Investor Services.

For the neural network part of the study, the data is divided 80:20, thus 80% of the data (the first 8 years) is used to predict known results for the last 20% (the last 2 years). In this study, only ordinary shares are considered.

The neural network used in this study utilizes the backpropagation model and implements a logistical sigmoid function as the activation function. The tool used to conduct this research was Neuro-Lab. Inputs to the

network are raw variables, rather than deltas. Typically, some form of normalization is needed, given the sensitivity of neural networks to outliers in the data. In this study, the full output range over the in-sample data was studied for every technical variable. All values which occurred less than 1% of the time were deemed as outliers, and excluded.

There are no standard rules available for determining the appropriate number of hidden layers and hidden neurons per layer. General rules of thumb have been proposed by a number of researchers. For example, Shih [20] suggests constructing nets to have a pyramidal topology, which can be used to infer approximate numbers of hidden layers and hidden neurons. Azoff [21] quotes a theorem due to Komolgorov that suggests a network with one hidden layer and  $2N + 1$  hidden neurons is sufficient for  $N$  inputs. Azoff concludes that the optimum number of hidden neurons and hidden layers is highly problem dependant, and is a matter for experimentation.

An alternative approach described by Tan [22], is to start with a small number of hidden neurons and increase the number of hidden neurons gradually. Tan’s procedure begins with 1 hidden layer, containing the square root of  $N$  hidden nodes, where  $N$  is the number of inputs. Training the network takes place until a pre-determined number of epochs have taken place without achieving a new low in the error function. At this point the network is tested against the in-sample set, and benchmarked. A new neural network is now created with the number of hidden nodes increased by 1, and the training and in-sample testing is repeated. After each test, the metric being used for benchmarking is assessed, to see if the new network configuration is superior. This process continues while the networks being produced are superior, that is, it terminates at the first network produced which shows inferior in-sample results.

To address the issues related to uncertainty of ANN configuration, Tan’s approach will be used to determine the correct number of hidden neurons. Training will take place until 2000 epochs have not produced a new error low. Each ANN architecture will be trained with unbounded input data, and then again with input data bounded to three standard deviations from the mean. In-sample results for the ASX Allshare will be presented for each configuration, and out-of-sample results will be presented for the best performing configuration.

The ANNs contained 17 data inputs. These are the technical variables deemed as significant from the review of both academic and practitioner publications. The formulas used to compute these variables are standard within technical analysis. The actual variables are:

- SMA(close,3) / SMA(close,15)
- ATR(3) / ATR(15)
- SMA(volume,3) / SMA(volume,15)

- ADX(3)
- ADX(15)
- STOCHK(3)
- STOCHK(15)
- STOCHK(3) / STOCHK(15)
- MOM(3)
- MOM(15)
- MOM(3) / MOM(15)
- RSI(3)
- RSI(15)
- RSI(3) / RSI(15)
- MACD
- LPR
- HPR

The acceptable range, and outlier range for each of these variables is presented below:

Technical Variable	Acceptable Range	Outliers
SMA(close,3) / SMA(close,15)	> 0.5 to <= 1.5	<= 0.5 or > 1.5
ATR(3) / ATR(15)	> 0 to <= 2.5	<= 0 or > 2.5
SMA(Volume,3) / SMA(Volume,15)	> 0 to <= 3.5	<= 0 or > 3.5
ADX(3)	> 10	<= 10
ADX(15)	> 0 to <= 60	<= 0 or > 60
STOCHK(3)	ANY	none
STOCHK(15)	ANY	none
STOCHK(3) / STOCHK(15)	<= 200	> 200
MOM(3)	> -20 to <= 20	<= -20 or > 20
MOM(15)	> -20 to <= 20	<= -20 or > 20
MOM(3) / MOM(15)	> -50 TO <= 50	<= -50 or > 50
RSI(3)	> 0	<= 0
RSI(15)	> 20 to <= 80	<= 20 or > 80
RSI(3) / RSI(15)	> 0 to <= 2	<= 0 or > 2
MACD	> -5 to <= 5	<= -5 or > 5
LPR	ANY	none
HPR	ANY	none

**Table 2 Technical Variables: Range and Outliers**

The basic statistical characteristics of the in-sample data are provided below:

Technical Variable	Min	Max	Mean	Stddev
SMA(close,3) / SMA(close,15)	0.51	1.50	1.00	0.08
ATR(3) / ATR(15)	0.00	2.48	0.94	0.38
SMA(Volume,3) / SMA(Volume,15)	0.00	3.50	0.97	0.63
ADX(3)	10.10	100.00	54.03	20.23
ADX(15)	1.31	59.92	23.42	9.86
STOCHK(3)	0.00	100.00	43.14	41.21
STOCHK(15)	0.00	100.00	45.70	33.72
STOCHK(3) / STOCHK(15)	0.00	75.00	1.00	1.41
MOM(3)	-12.00	5.98	0.00	0.26
MOM(15)	-17.99	14.94	-0.01	0.51
MOM(3) / MOM(15)	-45.00	45.00	0.18	1.50
RSI(3)	0.00	100.00	47.78	26.21
RSI(15)	20.23	80.00	49.31	10.64
RSI(3) / RSI(15)	0.00	2.00	0.93	0.43
MACD	-4.88	4.99	0.00	0.15
LPR	0.01	1.00	0.73	0.22
HPR	0.01	1.00	0.69	0.25

**Table 3 Technical Variables: Statistical Properties**

For completeness, the characteristics of the output target to be predicted, the 3 day return variable, are shown

below. This target is the maximum percentage change in price over the next three days, computed for every element  $i$  in the input series as:

$$\left( \frac{(\max(close_{i+3}, close_{i+2}, close_{i+1}) - close_i)}{close_i} \right) \times 100$$

**Equation 2 Maximum Price Change**

Effectively, this target allows the neural network to focus on the relationship between the input technical variables, and the expected forward price change.

Training Target	Min	Max	Mean	Stddev
Output Target	-85.71	200.00	2.99	9.84

**Table 4 Target Variable: Statistical Properties**

## 4. Results

A total of 1,222 securities (including delisted securities) had trading data during the test period, from which 19,458 input rows were used for training. These were selected by sampling the available datasets, and selecting every 50<sup>th</sup> row as an input row. Every 50<sup>th</sup> row roughly equates to every two months worth of trading data. The training range of the data is 8 years.

As previously explained, a number of hidden node architectures were created according to Tan's methodology. The characteristics of the architectures created, and the objective measures for each architecture are shown in Table 5. These objective measures are computed from the in-sample data.

ANN Architecture	Expectancy	Average Profit/Loss % (3 days)
4 hidden nodes	0.76	9.67%
5 hidden nodes	0.92	12.22%
6 hidden nodes	0.61	8.57%

**Table 5 In-Sample characteristics**

From this table, it is clear that the architecture with 5 hidden nodes is the appropriate architecture to be selected to proceed into system development.

## 5. Conclusion

The results demonstrate that ANNs can be trained to identify stocks with the potential to rise significantly, on the basis of the stocks technical attributes.

Figure 1 below shows a breakdown of the output values of the best performing neural network (scaled from 0 to 100) versus the average percentage returns for each network output value. The percentage returns are related

to the number of days that the security is held, and these are shown as the lines on the graph. Put simply, this graph visualizes the returns expected from each output value of the network and shows how these returns per output value vary with respect to the holding period.

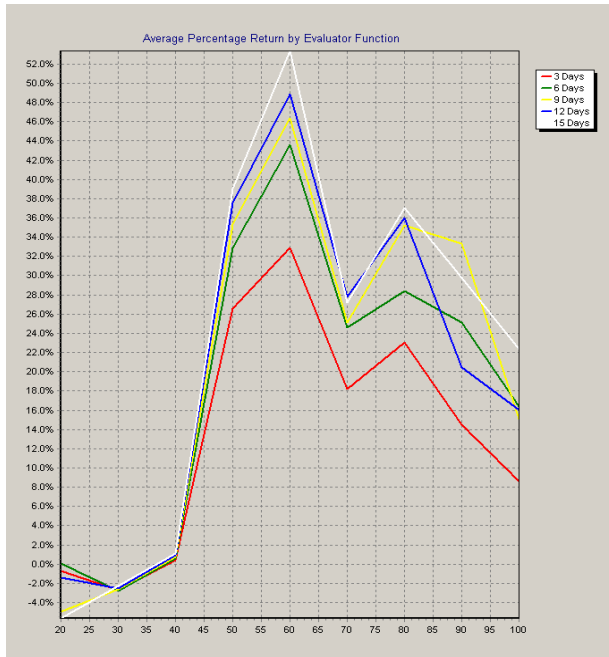


Figure 1 Percentage Returns by Output Value

## References

- [1] Vanstone, B., G. Finnie, and C.N.W. Tan, Applying Fundamental Analysis and Neural Networks in the Australian Stockmarket. *International Conference on Artificial Intelligence in Science and Technology (AISAT 2004)*, Hobart, Tasmania, 2004.
- [2] Tvede, L., *The Psychology of Finance* (Chichester: Wiley, 1999).
- [3] Warnecke, S.J., Hear this, Bob Prechter! A Critic attacks the Elliot Wave Theory, *Barron's*, January 26, 1987, 1987, 13.
- [4] Fama, E., The Behaviour of Stock Market Prices, *Journal of Business*, 1965, 34-105.
- [5] Taylor, M.P. and H. Allen, The Use of Technical Analysis in the Foreign Exchange Market, *Journal of International Money and Finance*, 11, 1992, 304-314.
- [6] Silber, W.L., *Technical Trading: when it works and when it doesn't*. Working Paper Series: Saloman Brothers Centre for the Study of Financial Institutions, Leonard N. Stern School of Business, New York University, 1993).
- [7] Pring, M.J., *Martin Pring's Introduction to Technical Analysis* (Singapore: McGraw-Hill, 1999).
- [8] Neftci, S.N. and A.J. Policano, Can Chartists outperform the Market? Market Efficiency tests for 'Technical Analysis', *Journal of Futures Markets*, 4(4), 1984, 465-478.
- [9] Murphy, J.J., *Intermarket Analysis*, *Intermarket*, 1988, 20-21.
- [10] Neftci, S.N., Naive Trading Rules in Financial Markets and Wiener-Kolmogorov Prediction Theory: A Study of 'Technical Analysis', *Journal of Business*, 1991, 549-571.
- [11] Brock, W., J. Lakonishok, and B. LeBaron, Simple Technical Trading Rules and the Stochastic Properties of Stock Returns, *Journal of Finance*, 47(5), 1992, 1731-1764.
- [12] Mills, T.C., Technical Analysis and the London Stock Exchange: Testing trading rules using the FT30, *International Journal of Finance and Economics*, 2, 1997, 319-331.
- [13] Levich, R. and L. Thomas, The significance of Technical Trading Rule Profits in the Foreign Exchange Markets: A Bootstrap Approach, *Journal of International Money and Finance*, 12, 1993, 451-474.
- [14] LeBaron, B., *Technical Trading Rules and Regime shifts in Foreign Exchange*, in *Advanced Trading Rules*, E. Acar and S. Satchell, Editors. 1997, Butterworth Heinemann.
- [15] Lehmann, B.N., Fads, Martingales and Market Efficiency, *The Quarterly Journal of Economics*, CV(1), 1990, 1-28.
- [16] Jegadeesh, N., Evidence of Predictable Behaviour of Security Returns, *Journal of Finance*, XLV(3), 1990, 881-898.
- [17] Wilder, J.W., *New Concepts in Technical Trading* (Greensboro, NC: Trend Research, 1978).
- [18] Siegel, J.J., *Stocks for the Long Run*. 3rd ed: McGraw-Hill, 2002).
- [19] Tharp, V.K., *Trade your way to Financial Freedom* (NY: McGraw-Hill, 1998).
- [20] Shih, Y., *Neuralyst Users Guide*: Cheshire Engineering Corporation, 1994).
- [21] Azoff, M.E., *Neural Network Time Series Forecasting of Financial Markets* (Chichester: Wiley, 1994).
- [22] Tan, C.N.W., *Artificial Neural Networks: Applications in Financial Distress Prediction and Foreign Exchange Trading* (Gold Coast, QLD: Wilberto Press, 2001).