

A Hybrid Financial Trading System Incorporating Chaos Theory, Statistical and Artificial Intelligence/Soft Computing Methods*

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Abstract: This paper proposes a hybrid financial trading system that incorporates the application of chaos theory, non-linear statistical models and artificial intelligence/soft computing methods, specifically, Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs). This proposal forms the basis for the research direction of the Advanced Investment Technology Group at Bond University and is currently under consideration in the final round for a large ARC grant application.

The methodology for this research can be defined in three phases. The first is in selecting the time series for modelling using chaos theory to identify time series that display non-random behavior. The second phase is in forecasting the time series using ANNs and non-linear statistical modelling techniques. The final phase is in implementing a rule-based financial trading system that incorporate the forecast with trading rules and a money management system that may incorporate the use of GAs.

An appendix on a primer on technical analysis, fundamental analysis, ANNs and trading systems as well as criteria for selection of data for ANN is provided.

Keywords: Financial trading system, Artificial Neural Networks, Chaos Theory, Hybrid Trading Systems, Time-Series methods, Forecasting.

JEL Classification Numbers: C45 - Neural Networks and Related Topics

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1 Introduction

1.1 Artificial Intelligence Applications in Finance

By and large, the evolution of commercial risk management technology has been characterized by computer technology lagging behind the theoretical advances of the field. As computers have become more powerful, they have permitted better testing and application of forecasting concepts. Recent years have seen a broadening of the array of computer technologies applied to forecasting. With the advent of the popularity of the Internet, data of various financial markets can be easily accessed. However, due to time and computational constraints, there still exist the need to select only a number of the time series from financial data that have the higher probability of providing abnormal returns.

One of the most exciting of these in terms of the potential for analyzing risk is Artificial Intelligence (AI)/Soft Computing and Nonlinear Statistical Forecasting methods. From the range of AI techniques, the one that deals best with uncertainty is Artificial Neural Network (ANN). Dealing with uncertainty with ANNs forecasting methods primarily involves recognition of patterns in data and using these patterns to predict future events. ANNs have been shown to handle time series problems better than other AI techniques because they deal well with large noisy data sets. Unlike expert systems, however, ANNs are not transparent, thus making them difficult to interpret. In our research proposal, we intend to use RULEX, a rule-extraction ANN program developed at the Queensland University of Technology that may enable the extraction of rules from the ANN model.

Expert systems and Artificial Neural Networks offer qualitative methods for business and economic systems that traditional quantitative tools in statistics and econometrics cannot quantify due to the complexity in translating the systems into precise mathematical functions.

While artificial intelligence techniques have only recently been introduced in finance, they have a long history of application in other fields. Experience to date across a wide range of non-financial applications has been mixed. Patrick Winston, a leading AI researcher and the head of MIT's AI Laboratory, conceded that the traditional AI methods such as search methods, predicate calculus, rule-based expert systems and game-playing, have achieved little progress [Gallant 1994]. The problem domain that traditional AI methods seem to fail in is in the trivial and common sense-type of tasks that humans find easy, such as recognizing faces, identifying objects and walking.

Therefore, it was natural for AI researchers to turn to nature and the physical laws and processes for inspiration to find better solutions. As a result, many of the contemporary artificial intelligence tools developed in the natural sciences and engineering field have successfully found their way into the commercial world. These include wavelet transformations and finite impulse response filters (FIR) from the signal processing/electrical engineering field; genetic algorithms and artificial neural networks from the biological sciences; and, chaos theory and simulated annealing from the physical sciences. These revolutionary techniques fall under the AI field as they represent ideas that seem to emulate intelligence in their approach to

solving commercial problems. All these AI tools have a common thread in that they attempt to solve problems such as the forecasting and explanation of financial markets data by applying physical laws and processes. Pal and Srimani [1996] state that these novel modes of computation are collectively known as *soft computing* as they have the unique characteristic of being able to exploit the tolerance imprecision and uncertainty in real world problems to achieve tractability, robustness, and low cost. They further state that soft computing is often used to find an approximate solution to a precisely (or imprecisely) formulated problem. Huffman [1994] of Motorola states that “At Motorola, we call neural networks, fuzzy logic, genetic algorithms and their ilk *natural computing*”.

These contemporary tools are often used in combination with one another as well as with more traditional AI methods such as expert systems in order to obtain better solutions. These new systems that combine one or more AI methods (which may include traditional methods) are known as ‘hybrid systems’. An example of a hybrid system is the financial trading system described in a paper by Tan [1995ab].

According to Zahedi [1993], expert systems and Artificial Neural Networks offer qualitative methods for business and economic systems that traditional quantitative tools in statistics and econometrics cannot quantify due to the complexity in translating the systems into precise mathematical functions.

Medsker et al. [1996] list the following financial analysis task on which prototype neural network-based decisions aids have been built:

- Credit authorization screening
- Mortgage risk assessment
- Project management and bidding strategy
- Financial and economic forecasting
- Risk rating of exchange-traded, fixed income investments.
- Detection of regularities in security price movements
- Prediction of default and bankruptcy

Hsieh [1993] states the following potential corporate finance applications can be significantly improved with the adaptation to ANN technology:

- Financial Simulation
- Predicting Investor’s Behavior
- Evaluation
- Credit Approval
- Security and/or Asset Portfolio Management

- Pricing Initial Public Offerings
- Determining Optimal Capital Structure

Trippi and Turban [1996] noted in the preface of their book, that financial organizations are now second only to the US Department of Defense in the sponsorship of research in neural network applications.

Despite the disappointing result from White's [1988] initial seminal work in using ANNs for financial forecasting with a share price example, research in this field has generated growing interest. Despite the increase in research activity in this area however, there are very few detailed publications of practical trading models. In part, this may be due to the fierce competition among financial trading houses to achieve marginal improvements in their trading strategies, which can translate into huge profits and their consequent reluctance to reveal their trading systems and activities.

This reluctance notwithstanding, as reported by Dacorogna et al. [1994], a number of academicians have published papers on profitable trading strategies even when including transaction costs. These include studies by Brock et al. [1992], LeBaron [1992], Taylor and Allen [1992], Surajaratne and Sweeney [1992] and Levitch and Thomas [1993].

From the ANN literature, work by Refenes et al.[1995], Abu-Mostafa [1995], Steiner et al.[1995], Freisleben [1992], Kimoto et al.[1990], Schoneburg [1990], all support the proposition that ANNs can outperform conventional statistical approaches.

Weigend et al. [1992] find the predictions of their ANN model for forecasting the weekly Deutshmark/US Dollar closing exchange rate to be significantly better than chance. Pictet et. al. [1992] reports that their real -time trading models for foreign exchange rates returned close to 18% per annum with unleveraged positions and excluding any interest gains. Colin [1991] reports that Citibank's proprietary ANN-based foreign exchange trading models for the US Dollar/Yen and US Dollar/Swiss Franc foreign exchange market achieved simulated trading profits in excess of 30% per annum and actual trading success rate of about 60% on a trade-by-trade basis. These studies add to the body of evidence contradicting the EMH.

2 Description of Proposed Hybrid System

Figure 1 in the next page shows the overall model of the proposed hybrid system incorporating chaos theory, artificial intelligence/soft computing and statistical methods for financial forecasting and trading.

We intend to use historical Australian and international stock market prices and foreign exchange rates to test our forecasting models and the trading system.

2.1 First Phase:-Selection of Financial Time Series using Chaos Theory

The first phase of the project will attempt to develop a methodology to select the financial time series data that has the most potential of being modeled to obtain abnormal returns. We hypothesize that if a financial time series is not random, but behaves in a random-like manner, it may be chaotic (hence, deterministic) and thus may be modeled by non-linear statistical or ANN models.

The first phase outcome will be a methodology to identify financial time series that may be deterministic or chaotic. Only financial time series that exhibit this behavior will be used in the second phase of the project, which is developing the forecasting model. We will assume that data that have been analyzed in phase one that are not deterministic are stochastic or random and hence, will not be considered for the forecasting models in the next phase of the research.

We will assume that the one dimensional time series is a projection from a multidimensional system. Therefore we need to reconstruct the series, to its true dimension. We will reconstruct the time series using the time delay and the embedding dimension parameters. Processing starts with the non-linear system detector part, consisting of various functional criteria. One of the function is to measure the Hurst exponent value (H) to determine whether the number of data set is adequate for measuring the Hurst exponent, and then calculating the mean orbital period and the overall nature of the time series, in other words its persistency and anti-persistency nature. We will analyze the methods of measuring the Hurst such as choosing a good compressor value, (i.e., log return is a very high compressor) for the time series, averaging for different N , thus removing the AR residual part, and the first peak from the data set of $\log(R/S)$ and $\log(N)$. From the value of H , we will then decide the type of model to use for fitting, i.e. a short term (e.g. ARIMA) or a long term (e.g. FARIMA) model.

The other functions that we will investigate are average mutual information, calculation of the minimum embedding dimension, and time delay to reconstruct the phase space. The simplest method of measuring the time delay is from the peak-to-peak analysis or time domain auto-correlation function. The system predictability is measured from recurrent analysis, rather than the time delay plot, on the basis of a parameter called spectral entropy. It is a very useful measure for selection of a financial time series from the historical database. We will attempt to develop a model, which preprocess the data in varying time window size, window gap and measure the dynamic nature of the system. We will then fit the appropriate model to that particular time frame. The idea is based on the concept that a time series changes its basic nature in mainly three forms: trending, chaotic or random. The change in the dynamic nature of the system is detected by calculating the largest Lyapunov exponent for different time window size. We will also investigate how the prediction error can be determined from the value of Lyapunov exponent.

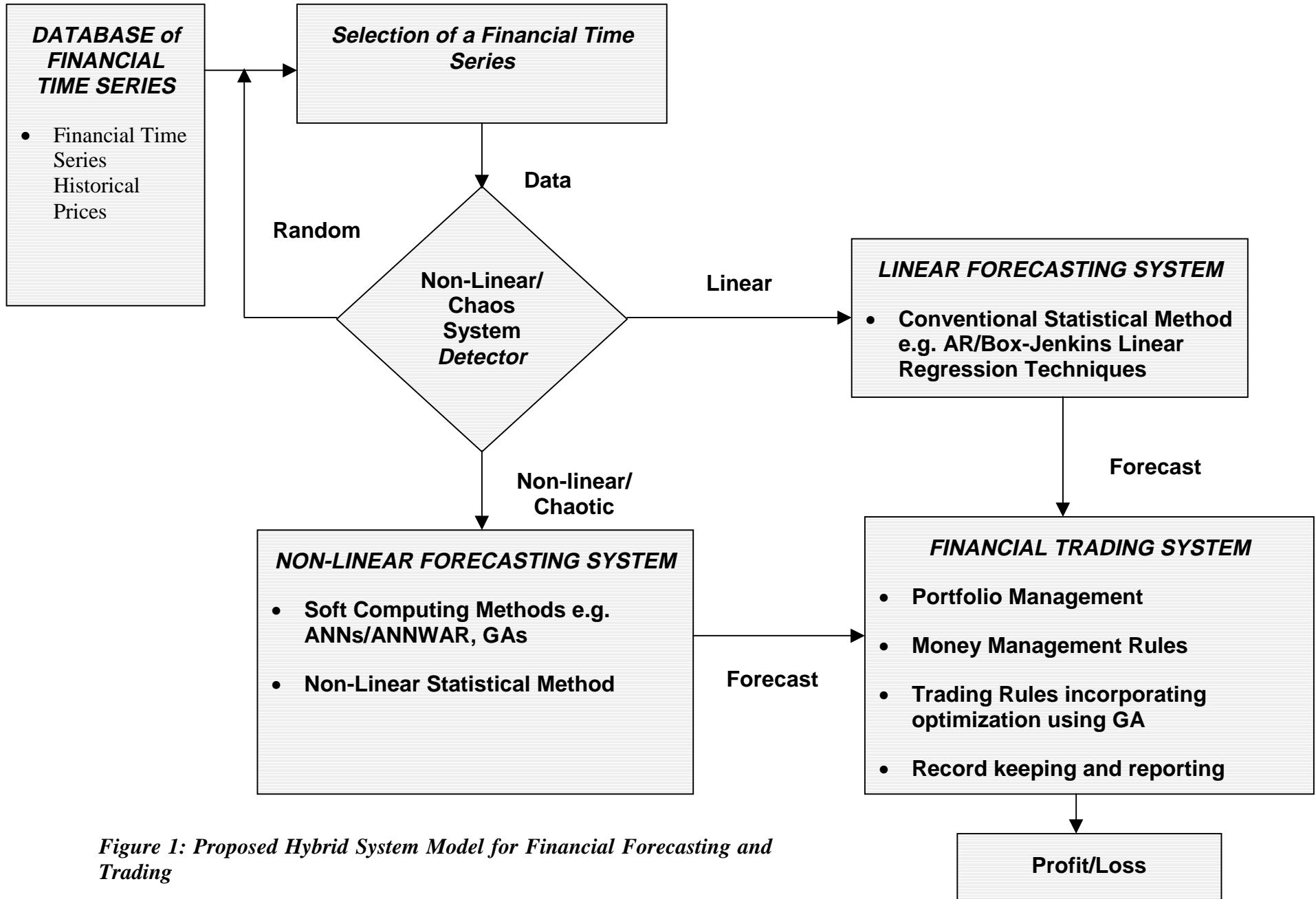


Figure 1: Proposed Hybrid System Model for Financial Forecasting and Trading

2.2 Second Phase:- Financial Forecasting Models using Non-linear Statistical and Soft Computing Methods

The second phase of the project will involve selecting and developing forecasting models based on the classification of the behavior of the financial time series analyzed in phase one. Financial time series that exhibit chaotic behavior will be used in this phase. This will involve applying soft computing methods, specifically Artificial Neural Networks and Genetic Algorithms, and non-linear statistical methods and combinations of the methodologies e.g. ANNWAR (ANN With AR) model first proposed by Tan [1995,1997] that incorporates the output of an AR model to an ANN to enhance the capability of the model. We intend to extend this method to ARCH and GARCH models.

2.2.1.1 Soft Computing Methods- Artificial Neural Networks

In traditional statistical analysis, the modeller is required to specify the precise relationship between inputs and outputs and any restrictions that may be implied by theory. ANNs differ from conventional techniques in that the analyst is not required to specify the nature of the relationships involved; the analyst simply identifies the inputs and the outputs. No knowledge of ANNs training methods such as back-propagation is required to use ANNs. In addition, the ANNs' main strength lies in its ability to vary in complexity, from a simple parametric model to a highly flexible, nonparametric model. For example, an ANN that is used to fit a nonlinear regression curve, using one input, one linear output, and one hidden layer with a logistic transfer function, can function like a polynomial regression or least squares spline. It has some advantages over the competing methods. Polynomial regression are linear in parameters and thus are fast to fit but suffers from numerical accuracy problems if there are too many wiggles. Smoothing splines are also linear in parameters and do not suffer from the numerical accuracy problems but pose the problem of deciding where to locate the knots. ANNs with nonlinear transfer function, on the other hand, are genuinely nonlinear in the parameters and thus require longer computational processing time. They are more numerically stable than high-order polynomials and do not require knot location specification like splines.

2.3 Constructing the ANN

The ANN time series modeling technique will be similar to those done by Tan [1993ab, 1995ab] on forecasting financial time series.

Setting up an ANN is essentially a 4 step procedure.

Firstly, the data to be used need to be defined and presented to the ANN as a pattern of input data with the desired outcome or target.

Secondly, the data are categorized to be either in the training testing or validation (out-of-sample) set. The ANN only uses the training set in its learning process in developing the

model. The test set is used to test the model for its predictive ability and when to stop the training of the ANN.

Thirdly, the ANN structure is defined by selecting the number of hidden layers to be constructed and the number of neurons for each hidden layer.

Finally, all the ANN parameters are set before starting the training process.

As there are no fixed rules in determining the ANN structure or its parameter values, a large number of ANNs may have to be constructed with different structures and parameters before determining an acceptable model. The trial and error process can be tedious and the experience of the ANN user in constructing the networks is invaluable in the search for a good model.

Determining when the training process needs to be halted is of vital importance in obtaining a good model. If an ANN is overtrained, a curve-fitting problem may occur whereby the ANN starts to fit itself to the training set instead of creating a generalized model. This typically results in poor predictions of the test and validation data set. On the other hand, if the ANN is not trained for long enough, it may settle at a local minimum, rather than the global minimum solution. This typically generates a sub-optimal model. By performing periodic testing of the ANN on the test set and recording both the results of the training and test data set results, the number of iterations that produces the best model can be obtained. All that is needed is to reset the ANN and train the network up to that number of iterations.

2.4 Third Phase:- Financial Trading and Portfolio Management System

Though the profitable speculation depends on accurate price rate forecasting, in reality it is very hard to achieve. Financial trading systems can reduce the reliance on the accuracy of the forecast in improving returns by managing the risk to return ratio. The key to profits is not to anticipate trends, but to follow them [Babcock 1989]. According to Babcock, a mechanical approach is the only way to avoid the destructive emotionalism that permeates trading, which perhaps explain why trading systems can enhance profitability in trading.

Transaction costs such as slippage and commissions are an overhead cost that must be added to every trade. Many of the past research in trading systems that reported amazing success excluded transaction costs. If the costs were taken into account, most of these systems will fail to provide an abnormal return. However, there is work done that reported successful returns with costs taken into account such as Tan [1995ab]. Our research will follow on Tan's work and will take into account all transaction costs.

In the third and final phase of our research, we will develop a set of rules to perform money management, portfolio and risk management, signals the trades (if any) to be done and reports the profit pr loss of the overall system. The portfolio management module will combine various financial time series that have been identified in Phase 2 of the project as having the potential to return abnormal profits, to see if an optimal risk/return

ratio can be found. We intend to optimize the portfolio selection using Genetic Algorithms. We will use the conventional Markowitz's model to benchmark against the optimized portfolio.

The money management module will be designed to optimize the amount of funds to be committed for each trade based on the forecast strength of the second phase, amount of total funds currently available, the maximum amount of drawdown that is allowed, etc.

The trading rules modules will be analyze for optimal return and we may use Genetic Algorithms to select technical indicators for the rules as well as find the optimal parameters for those technical indicators. Technical indicators that we may use include: moving averages, oscillators e.g. momentum and stochastic, directional movement indicators, etc. The simple rules that have been used in Tan's [1995ab] models consisted of buying or selling a security if the forecast from the models were higher or lower than the current prices by a certain factor. The factors include transaction costs and filter values that were used to eliminate trades that have small amount of forecast price movements.

The last module is the record keeping and profit or loss reporting. We intend to design this model to be as flexible as possible in terms of adding parameters such as variable transactions costs (as this can vary depending on the financial security that is being traded), amount of risk tolerance desired (i.e., aggressive or risk averse), number of successive trading losses to be tolerated, maximum amount of loss per trade, etc. The reporting module will not only report the net amount of profit or loss but identify other benchmark measurements such as best/worst trade, profit/loss per trade, etc. as identified by Refenes [1995].

3 Benefits of Research

This project will result in fundamental advances in non-linear time series modelling and forecasting. It will suggests the possible class of various modelling techniques incorporating soft computing techniques and non-linear statistical modelling for forecasting Australian stock data, Australian foreign exchange rate data, currency data and other economic, financial and environmental time series data.

The significance of this research is that it will:

- determine a methodology for selecting stocks/indices that have a higher probability of providing abnormal returns,
- contribute to the understanding of how chaos theory and artificial intelligence/soft computing methods can be applied to financial time series forecasting, and
- assist in the understanding and the determination of the appropriate forecasting methods to use for making financial decisions involving forecasting,
- formalize a methodology in the design of a hybrid financial trading system that can make abnormal returns for a given amount of risk.

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Appendix A: Introduction to Trading Techniques-Technical Analysis, Fundamental Analysis, Trading System and Data Selection Criteria

The techniques applied by traders broadly fall into two main categories, technical analysis and fundamental analysis. The trading system that is described in this chapter falls under the technical analysis technique.

1 Technical Analysis

Technical analysis (TA) is defined as the study of *market (price) action*¹ for the purpose of forecasting future price trends [Murphy 1986]. It is probably the most widely used decision making tool for traders who make multi-million dollar trading decisions.

According to Davidson [1995], the Bank of England reported in its quarterly bulletin in November 1989 that 90% of foreign exchange dealing institutions uses some form of charting or technical analysis in foreign exchange trading with two thirds claiming charts are as important as fundamentals for short-term forecasting (intraday to one week). He concludes that, since intraday traders account for 90% of the foreign exchange volume, technical analysis plays an important role in decision making in the market.

One of the reason for TA's popularity is that it forces a discipline and control on trading by providing traders with price and profit/loss objectives before trades are made. It is also a very useful tool for short-term as well as long-term trading strategies as it does not rely on any information other than market data. Another reason for its popularity is that, while its basic ideas are easy to understand, a wide variety of trading strategies can be developed from these ideas.

Currently the major areas of technical analysis are:

1. *Charting*: The study of price charts and chart patterns; e.g. trendlines, triangles, reversal patterns, and Japanese candlesticks.
2. *Technical/Statistical Indicators*: The study of technical indicators; e.g., momentum, relative strength index (RSI), stochastic and other oscillators.
3. *Trading Systems*: Developing computerized or automated trading systems, as well as mechanical trading systems, ranging from simple systems using technical indicators with a few basic rules (to generate trading signals such as moving averages) to complex rule-based systems incorporating soft computing methods such as artificial neural networks, genetic algorithms, and fuzzy logic. The traditional trading systems are based on rigid rules for entering and exiting the

¹ Although the term “price action” is more commonly used, Murphy [1986] feels that the term is too restrictive to commodity traders who have access to additional information besides price. As his book focuses more on charting techniques for commodity futures market, he uses the term “market action” to include price, volume and open interest and it is used interchangeably with “price action” throughout the book.

market. The main advantage of these systems is that they impose discipline on traders using them to be discipline.

4. *Esoteric methods* e.g. Elliot Waves, Gann Lines, Fibonacci ratios, and astrology.

Murphy [1986] summarizes the basis for technical analysis into the following three premises:

- *Market action discounts everything.*

The assumption here is that the price action reflects the shifts in demand and supply which is the basis for all economic and fundamental analysis and everything that affects the market price is ultimately reflected in the market price itself. Technical analysis does not concern itself in studying the reasons for the price action and focuses instead on the study of the price action itself.

- *Prices move in trends.*

This assumption is the foundation of almost all technical systems that try to identify trends and trading in the direction of the trend. The underlying premise is that a trend in motion is more likely to continue than to reverse.

- *History repeats itself*

This premise is derived from the study of human psychology which tends not to change over time. This view of behavior leads to the identification of chart patterns that are observed to recur over time, revealing traits of a bullish or a bearish market psychology.

2 Fundamental Analysis

Fundamental analysis studies the effect of supply and demand on price. All relevant factors that affect the price of a security are analyzed to determine the intrinsic value of the security. If the market price is below its intrinsic value then the market is viewed as undervalued and the security should be bought. If the market price is above its intrinsic value, then it should be sold.

Examples of relevant factors that are analyzed are financial ratios; e.g. Price to Earnings, Debt to Equity, Industrial Production Indices, GNP, and CPI. Fundamental analysis studies the causes of market movements, in contrast to technical analysis, which studies the effect of market movements. Interest Rate Parity Theory and Purchasing Power Parity Theory are examples of the theories used in forecasting price movements using fundamental analysis.

The problem with fundamental analysis theories is that they are generally relevant only in predicting longer trends. Fundamental factors themselves tend to lag market prices, which explains why sometimes market prices move without apparent causal factors, and the fundamental reasons only becoming apparent later on. Another factor to consider in fundamental analysis is the reliability of the economic data. Due to the complexity of today's global economy, economic data are often revised in subsequent periods therefore posing a threat to the accuracy of a fundamental economic forecast that bases its model on the data. The frequency of the data also pose a limitation to the predictive horizon of the model.

3 ANNs and Trading Systems

Today there are many trading systems being used in the financial trading arena with a single objective in mind; that is; to make money. Many of the trading systems currently in use are entirely rule-based, utilizing buy/sell rules incorporating trading signals that are generated from technical/statistical indicators such as moving averages, momentum, stochastic, and relative strength index or from chart patterns formation such as head and shoulders, trend lines, triangles, wedge, and double top/bottom.

The two major pitfalls of conventional rule-based trading systems are the need for an expert to provide the trading rules and the difficulty of adapting the rules to changing market conditions. The need for an expert to provide the rules is a major disadvantage in designing a trading system as it is hard to find an expert willing to impart his/her knowledge willingly due to the fiercely competitive nature of trading. Furthermore, many successful traders are unable to explain the decision-making process that they undergo in making a trade. Indeed, many of them just put it down to '*gut feel*'². This makes it very difficult for the knowledge engineer³ to derive the necessary rules for the inference engine⁴ of an expert system to function properly.

The inability to adapt many rule-based systems to changing market conditions means that these systems may fail when market conditions change; for example, from a trending market to a non-trending one. Different sets of rules may be needed for the different market conditions and, since markets are dynamic, the continuous monitoring of market conditions is required. Many rule-based systems require frequent optimization of the parameters of the technical indicators. This may result in curve fitting of the system.⁵

ANNs can be used as a replacement of the human knowledge engineer in defining and finding the rules for the inference engine. An expert's trading record can be used to train an ANN to generate the trading rules [Fishman 1991]. ANNs can also be taught profitable trading styles using historical data and then used to generate the required rules. In addition, they can learn to identify chart patterns, thereby providing valuable insight for profitable trading opportunities. This was demonstrated by Kamijo and Kanigawa [1990] who successfully trained a neural network to identify triangular patterns of Japanese candlestick charts.

Finally, ANNs which are presented with fundamental data can find the rules that relate these fundamental data (such as GNP, interest rates, inflation rates, unemployment rates, etc.,) to price movements. Freisleben [1992] incorporated both technical and fundamental analysis in his stock market prediction model while Kimoto and Asakawa

² It is interesting that some recent studies have linked the neurons in the brain to activities in the stomach. Therefore, the term '*gut feel*' may be more than just a metaphor!

³ A knowledge engineer is a term used to describe expert system computer programmers. Their job function is to translate the knowledge they gather from a human expert into computer programs in an expert system.

⁴ The inference engine is a computer module where the rules of an expert system are stored and used.

⁵ A system is said to be curve fitting if excellent results are obtained for only a set of data where the parameters have been optimized but is unable to repeat good results for other sets of data.

[1990] used fundamental/economic data such as interest rate and foreign exchange rate in their forecasting model. The research reported in this thesis incorporates technical analysis into an ANN, to the extent that it incorporates historical price data and a statistical value (from the AR model).

4 Basic Structure of a Rule-based Financial Trading System

The two possible trading actions and the associated minimum basic rules for a financial trading system are:

- 1) Opening a position:
 - a. Buy rule
 - b. Sell rule
- 2) Closing a position
 - a. Stop/Take Profit rule

According to R. S. Freedman [Freedman 1991], the two general trading rules for profiting from trading in securities markets are:

- i Buy low and sell high.
- ii Do it before anyone else.

Most trading systems are trend following systems, e.g., moving averages and momentum. The system works on the principle that the best profits are made from trending markets and that markets will follow a certain direction for a period of time. This type of system will fail in non-trending markets. Some systems also incorporate trend reversal strategies by attempting to pick tops or bottoms through indicators that signal potential market reversals. A good system needs to have tight control over its exit rules that minimize losses while maximizing gains.

4.1 Opening Position rules

Only one of the following rules below can execute for a specific security at any one time, thus creating an open position. None of these rules can be executed for a security that has an existing open position. A position is opened if there is a high probability of a security price trending. A position is said to be *open* if either a buy or a sell rule is triggered.

a. Buy Rule

This rule is generated when the indicators show a high probability of an increase in the price of the security being analyzed. Profit can be made by buying the security at this point in time and selling it later after the security price rises. Buying a security opens a *long* position.

b. Sell Rule

This rule is generated when the indicators show a high probability of a drop in price of the security being analyzed. Profit can be made by selling the security at this point in time and buying it later after the security price declines. Selling a security opens a *short* position.

4.2 Closing Position rules

A position can only be closed if there is an open position. A position is closed if there is a high probability of a reversal or ending of a trend.

a. Stop/Take Profit rule

This rule can only be generated when a position (either long or short) has been opened. It is generated when indicators show a high probability of a reversal in trend or a contrary movement of the security price to the open position. It can also be generated if the price of the security hits a certain level thus causing the threshold level of loss tolerance to be triggered.

Systems that set a profit-taking target when a position is open call the closing position rule, a take-profit rule, while systems that place stops on an open position call the closing position rule a stop loss rule.

Chart 4-1 is an example of the technical charts analyzed by traders for pattern formations such as head and shoulders, triangles, and trend lines. The main components of the chart are the high, low and closing price of the security plotted against time. Sometimes the opening price and volume of transactions completed are also plotted. For a profitable trade to be made, it is obvious that one needs to buy when the price has bottomed out and sell when the price has topped out.

Chart 4-1

A Typical Technical Price Chart

Citicorp Share Price (US Dlr) Feb. 1987 - April 1992



5 Selection of Indicators/Data Input to ANN

The selection of technical and economic indicators/data to be used will depend on the following factors:

i. Availability:

The data must be easily obtainable.

ii. Sufficiency of the historical databases:

There must be enough sample data for the ANN learning and system testing process.

iii. Correlation of the indicators to the price:

The data should have some relevancy to the price of the security (whether it is lagging, leading, coincidental or noise).

iv. Periodicity of the data:

The data must be available in a predictable frequency (quarterly, monthly, weekly, yearly).

v. Reliability of the data:

The fast changing pace of today's global financial world and the increased in financial market volatility has resulted in difficulty to obtain reliable economic data. This results in economic bodies having to frequently revise their data. Thus, if a price forecasting model is built on revised historical input data, the model's immediate forecast may not be reliable as the new data that is fed into the model will probably be erroneous.

Two sets of historical data are used. The first set is used to train the ANN to develop trading strategies and generate rules. The second set is used to test the profitability and reliability of the system. The system developer must be careful not to use the second set as training data inadvertently by modifying the system if it performs badly on the second set of data.