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Competitive Co-Evolution of Trend Reversal Indicators Using Particle Swarm Optimisation

by

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Abstract

Computational Intelligence has found a challenging testbed for various paradigms in the financial sector. Extensive research has resulted in numerous financial applications using neural networks and evolutionary computation, mainly genetic algorithms and genetic programming. More recent advances in the field of computational intelligence have not yet been applied as extensively or have not become available in the public domain, due to the confidentiality requirements of financial institutions.

This study investigates how co-evolution together with the combination of particle swarm optimisation and neural networks could be used to discover competitive security trading agents that could enable the timing of buying and selling securities to maximise net profit and minimise risk over time. The investigated model attempts to identify security trend reversals with the help of technical analysis methodologies.

Technical market indicators provide the necessary market data to the agents and reflect information such as supply, demand, momentum, volatility, trend, sentiment and retracement. All this is derived from the security price alone, which is one of the strengths of technical analysis and the reason for its use in this study.

The model proposed in this thesis evolves trading strategies within a single population of competing agents, where each agent is represented by a neural network. The population is governed by a competitive co-evolutionary particle swarm optimisation algorithm, with the objective of optimising the weights of the neural networks. A standard feed forward neural network architecture is used, which functions as a

market trend reversal confidence. Ultimately, the neural network becomes an amalgamation of the technical market indicators used as inputs, and hence is capable of detecting trend reversals. Timely trading actions are derived from the confidence output, by buying and short selling securities when the price is expected to rise or fall respectively.

No expert trading knowledge is presented to the model, only the technical market indicator data. The co-evolutionary particle swarm optimisation model facilitates the discovery of favourable technical market indicator interpretations, starting with zero knowledge. A competitive fitness function is defined that allows the evaluation of each solution relative to other solutions, based on predefined performance metric objectives. The relative fitness function in this study considers net profit and the Sharpe ratio as a risk measure.

For the purposes of this study, the stock prices of eight large market capitalisation companies were chosen. Two benchmarks were used to evaluate the discovered trading agents, consisting of a Bollinger Bands/Relative Strength Index rule-based strategy and the popular buy-and-hold strategy. The agents that were discovered from the proposed hybrid computational intelligence model outperformed both benchmarks by producing higher returns for in-sample and out-sample data at a low risk. This indicates that the introduced model is effective in finding favourable strategies, based on observed historical security price data. Transaction costs were considered in the evaluation of the computational intelligent agents, making this a feasible model for a real-world application.

Keywords:
Evolutionary Computation, Competitive Co-Evolution, Particle Swarm Optimisation, Artificial Neural Networks, Finance, Stock Exchange Trading, Technical Market In-

dicators, Technical Analysis

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Chapter 1

Introduction

1.1 Problem Statement and Overview

The timing when to buy and sell securities is known to be a difficult task. Estimating the rise and fall of the price of a security is non-trivial, due to security price fluctuations, which can be caused by several factors. Price fluctuation factors may include the supply and demand of the security, stock market cycles, the behaviour of investors, market news, company performance, financial announcements, dividend declarations, dividend payments, interest rates, foreign exchange rates and commodity prices. Combining all these factors into one coherent decision-making model is a daunting task.

Technical analysis (TA) simplifies the problem at hand by allowing one to focus solely on the actual security price, rather than several factors that could possibly constitute a change in price. The main concept behind TA is that price discounts everything, meaning that all price fluctuation factors are incorporated into the price of a security. Based on this concept, the technical analyst concentrates on past and current security prices in order to estimate a possible price direction. Using the features that TA has to offer, this thesis aims to define a hybrid computational

intelligence (CI) model that trains a standard feed forward neural network (FFNN). The FFNN acts as the stock trading agent with the ability to detect market trend reversals and time stock transactions to produce profitable trades at low risk. The hybrid CI model consists of a competitive co-evolutionary particle swarm optimisation (CEPSO) algorithm. Technical market indicators (TMI) form a set of tools that aid technical analysis. Four TMIs have been chosen for this thesis, namely the Aroon, Bollinger Bands, Moving Average Convergence/Divergence and Relative Strength Index.

In more detail, the FFNN agent functions as a security trend reversal confidence. Given the information provided by the four TMIs, the agent can estimate with a certain degree of confidence when an up-trend market is about to switch to a down-trend and vice versa. The advantage of using a neural network (NN) is that it allows a non-linear interpretation of the TMI data, which would be impossible for human experts to derive. Representing the trading agents as NNs offers flexibility when different TMIs are to be introduced, which could easily be done by adding new input units to the neural network architecture. Another advantage representing agents as a NN includes the capability of the NN agent to weight the influence of TMIs with regards to the trend reversal confidence output. This means that the FFNN strategies discovered by the CEPSO model only considers the TMI information to the extent that the information is beneficial to the trading strategy.

The competitive co-evolutionary environment consists of a single population of strategies representing the FFNN trading agents. Co-evolution offers an environment within which strategies are evaluated against each other and scored accordingly on their performance over competing strategies. A relative competitive fitness function is defined for the purpose of scoring the strategies. This function allows the evaluation of each solution relative to other solutions, based on predefined performance metric objectives. The relative competitive fitness function in this study considers net profit

and the Sharpe ratio as a risk measure.

The CEPSO model used to discover stock trading models offers many advantages over conventional TMI rule-based models. TMI rule-based models require the careful selection of indicators and the definition of rules that allows the logical interaction of the indicators to produce sound trade actions. Apart from various parameters that define these TMIs, not much can be done to fine-tune models for different securities. The CEPSO model that is presented in this study allows the easy introduction of any number of TMIs. No expert trading knowledge is needed for training or defining trading rules. The model can search for the optimal solution in hyperspace, discovering complex strategies for individual securities. Each strategy returned is optimal to a specific security that can be used to derive high-profit and low-risk trading actions.

It is important that the discovered trading agents consider transaction costs when evaluated against benchmarks. Fees charged for stock buying and short selling are reflected in this work. The agents are compared against two benchmarks, consisting of a Bollinger Bands/Relative Strength Index rule-based strategy and the buy-and-hold strategy. The intelligent trading agents produced significantly higher overall returns compared to both of the chosen benchmarks, indicating the quality of discovered strategies.

1.2 Objectives

There are two main objectives that this thesis aims to accomplish:

- To study and define a co-evolutionary particle swarm optimisation model that can be used to optimise a neural network to detect trend reversals, used for security trading purposes.

- To examine whether technical market indicators can provide sufficient information to derive intelligent trading models using historical stock price data.

Furthermore, to study whether such models reflect high profitability and low risk when they are applied to newly introduced data not used for training.

Secondary objectives include the following:

- To present a background study on stock trading, technical market indicators and computational intelligence paradigms that are relevant to this study.
- To discover a competitive fitness function that incorporates profit and risk to allow the co-evolutionary particle swarm optimisation model to discover favourable solutions.
- To fine tune algorithm architectures and parameters to discover a set-up that has the ability to return the best solution, most consistently and with the least computational complexity.
- To investigate other security trading models and to compare these with the introduced model.

1.3 Contribution

The contribution of this study includes:

- The first application of a co-evolutionary particle swarm optimisation model in evolving stock trading agents starting from zero knowledge.
- The first effort in using computational intelligence to produce a security trend reversal indicator from which trading rules could be derived.
- The discovery of stock trading models that outperform the buy-and-hold strategy, including transaction costs. The performance of the models highlights their use as potential candidates for real-world application.

- The definition of a competitive relative fitness function for security trading strategies.

- The preferred security trading type for most computational intelligence work is mainly on index and foreign exchange data. This study deviates from this, using individual stock price data. This serves as an indication that technical analysis with computational intelligence could be used to derive profitable stock trading strategies for individual stocks.

- Stock short selling and buying back was included into the discovered security trading models, allowing the freedom to exploit more profitable opportunities. This is a noteworthy addition to the standard stock buying and selling that is commonly used.

1.4 Outline

The remainder of this thesis is organised as follows:

Chapter 2 covers background on the financial aspects of this thesis. An introduction to stock markets, and how a profit could be realised via stock transactions, is presented. The stock market, stock properties and market dynamics are also presented, giving the reader a clear understanding of stock market mechanics. The chapter additionally covers technical analysis, introducing principles and theories on the topic.

Chapter 3 builds on the technical analysis knowledge covered in the previous chapter. An introduction to the technical analysis methodology of using technical market indicator tools is made. Technical market indicators are defined, the purpose of using such indicators and how technical market indicators can be used to derive security-related information are covered in depth. The four technical market indicators selected for this thesis are presented, including Aroon, Bollinger Bands, Relative

Momentum Index and Moving Average Convergence/Divergence. For each indicator, a separate section describes the indicator, associated mathematical formulae, default parameter values and derived trading rules.

The work in this thesis involves three different computational intelligence paradigms, which are discussed in chapter 4. These paradigms include artificial neural networks, particle swarm optimisation and co-evolution. The chapter firstly focuses on the artificial neural network by presenting artificial neurons, activation functions, neural network learning approaches and architectures. Particle swarm optimisation is then discussed, including neighbourhood topologies, the PSO algorithm and various PSO related parameters. Co-evolution is then discussed, introducing competitive and cooperative co-evolution, competitive fitness, fitness evaluation, fitness sampling and the hall of fame. Relevant applications for each introduced paradigm are given, highlighting financial applications that are related to this study.

The presentation of the CEPSO model that is used to optimise the FFNN trading agents is done in chapter 5. The chapter explains why the specific model was chosen and describes advantages over traditional TMI rule-based strategies. A step-by-step listing of the model is provided in the chapter, introducing an overview of the model. The chapter further covers the trade simulation environment within which trading strategies are simulated. An explanation on how trade actions are derived from the FFNN follows, together with a description of how capital gains/losses, transaction costs and returns are calculated. A fundamental part of the CEPSO model is discussed in this chapter, by defining the competitive relative fitness function that is used in the co-evolutionary environment. A detailed description of the CEPSO model then follows.

The empirical study of the model follows in chapter 6, with the performance of the CEPSO model being closely examined. The model is applied to the stock price data of eight different companies, defined in the chapter. The topics of the

technical market indicator time series used and how the data is prepared for the model, are discussed. Experimental objectives are clearly stated, and the empirical study conducted. Different algorithm parameters and configurations are examined, with the optimum set-up determined. The best strategies are compared against two benchmarks at the end of the chapter, highlighting the effectiveness of the CEPSO model.

Chapter 7 concludes the thesis. A summary of the work is presented, highlighting what has been achieved and other noteworthy findings. Finally, the last section comments on future research ideas that could be applied to extend the work produced in this study.

Chapter 2

Stock Trading with Technical Analysis

The purpose of this chapter is to explain stock trading and technical analysis. Section 2.1 describes stock markets and how a profit could be realised via stock transactions. The stock market, stock properties and market dynamics are also covered, giving the reader a clear understanding of stock market mechanics. Section 2.2 explains the impact of technological advancements in the financial sector and how these have facilitated stock trading. Section 2.3 covers technical analysis, describing its principles and various theories on the topic. Section 2.4 touches upon fundamental analysis and describes its differences from technical analysis.

2.1 Stock Market

This section describes stock markets and how a profit could be realised via stock transactions. Stock properties and market dynamics are also covered, giving the reader an understanding of stock market mechanics. The section also explains the impact of technological advancements in the financial sector and how these have

facilitated stock trading.

2.1.1 Introduction

The term *stock market* is a general term referring to the mechanism of organised trading of *securities*. Stock markets allow buyers and sellers to get together and participate in the exchange of securities in an efficient manner, while obeying certain rules and regulations. A security is defined as an instrument representing [67]:

- **Ownership**: Stocks fall into this category, and are described in more detail in the next section.
- **Debt agreement**: Bonds represent a dept agreement. Investors who buy bonds are actually lending capital to the bond issuer. The issuer agrees on fixed amounts to be paid back to the investor on specific days.
- **The rights to ownership**: Derivatives represent the right of ownership, which derive their value by reference to an underlying asset or index.

Securities are commonly issued by a government, a corporation or any other organisation in order to raise capital.

2.1.2 Stock Properties

Stocks are also called shares or equities and are listed by public limited companies on a stock market. The purchase of stocks represents ownership in the company itself. Stock investors and hedge fund traders around the globe continuously exchange stocks at different price levels. Different types of shares exist, but the most common type is referred to as *ordinary shares* or *common stock*.

Only ordinary shares are considered in this study. A description of ordinary share characteristics and monetary returns is given here to explain how these shares can be used to realise a profit. Ordinary shares have the following characteristics:

- **Perpetual claim**: Individual shareholders can liquidate their investments in the share of a company only by selling their investment to another investor.

- **Residual claim**: Ordinary shareholders have a claim on the income and net assets of the company after obligations to creditors, bond holders and preferred shareholders have been met.

- **Limited liability**: The most that ordinary shareholders can lose if a company is formally disbanded is the amount of their investment in the company.

The monetary returns of ordinary shares consist of the following:

- **Stock dividends**: Dividend payouts are usually proportional to the company's profits. Dividends are not guaranteed until declared by the company's board of directors.

- **Capital gain/loss**: Capital gains or losses arise through changes in the price level of the company's stock. A capital gain is achieved by buying shares at a certain level and selling them at a higher price. Selling at a lower level than the level at which the shares were bought entails a capital loss.

  It is important to note that capital gains can also be achieved by selling shares that have not been previously purchased. This is done via *script lending*, also referred to as *short selling*. Script lending enables investors to borrow shares that they do not own and then sell the shares to other market participants. These shares must be bought back in future and returned to their original owners. The original owners charges a fee per share borrowed as a kickback. Capital gains (losses) are achieved by selling the shares at a certain price level and buying them back at a lower (higher) price level. The script lending fee is naturally also considered in the realisation of capital gains or losses.

2.1.3 Market Dynamics

Making a profit on a stock exchange can naively be filtered down to one single principle, namely buying at a low price and then selling at a higher price (or alternatively, short selling at a high price and then buying back at a lower price, via script lending). However, this simplistic statement is debatable, since it makes no reference to a number of important factors that could lead to price fluctuations. It is widely accepted that the following factors could lead to price fluctuations:

- The supply and demand of shares.
- Business and stock market cycles.
- Rational and irrational behaviour of investors and traders.
- Market news.
- Company performance and financial announcements.
- Dividend declarations and payments.
- Fluctuations in interest rates.
- Fluctuations in foreign exchange rates.
- Fluctuations in commodity prices.

The above statement outlines the most basic principle that the models discussed in this thesis attempt to exploit. Understanding this principle is very straightforward, but building a model to identify relatively low and high security price levels is a non-trivial task. Additionally, no such model can be regarded in any way as flawless. Building a profitable model today does not ensure profitability indefinitely into the future. The market is a dynamic environment with a mind of its own. From time to time the market may move in alignment with popular belief, but in general the

underlying governing factors that dictate its movements are unknown, irrational and increasingly difficult to predict. The popularity of static models has diminished over time and has left much to be desired. The appetite for improved models has given rise to a new breed of methodologies that will need to:

- Dynamically adjust the models based on current market conditions.
- Consider all the price fluctuation factors mentioned above.
- Provide a confidence level with each returned action. The confidence level indicates the certainty associated to the action. This confidence value could be interpreted as either a risk factor or as a probability of the accuracy of the returned action.

Development and utilisation of such dynamic and complex models was impossible in the past, mainly due to the non-availability and cost of technology. With the technological advancements in the past two decades, a new era in securities trading has dawned. It is widely accepted that we are now in the era of computer automation and machine trading [148][153][155][156].

2.2 Computer Automation and Machine Trading

The advancement of technology and the exponential increase in computational power has affected all business sectors, and the financial sector is no exception. The computer age has changed the way trading takes place [85, 87, 113]. Sophisticated software now assists traders and has replaced numerous time-consuming manual tasks. Stock charts that traders once plotted manually can now be displayed and modified instantly to allow traders to make faster and more confident decisions. With computational power becoming more affordable over time, financial institutions are now able to set up systems that can process more data, faster and much more cheaply,

and identify investment opportunities that once would have gone unnoticed. The counter effect of the exploitation of every opportunity has resulted in diminishing opportunities, making it ever more difficult to maintain a competitive edge over other competitors. One discipline that has enormously benefited from the computer age is that of technical analysis, which is described in detail in the next section.

2.3 Technical Analysis

This section covers technical analysis, describing principles and theories on the topic. The Dow Theory is explained, a defining theory for technical analysis. This section further discusses the controversy around technical analysis over the past few years.

2.3.1 Introduction

Technical analysis (TA) [13, 31, 45, 121] is a technique that uses historic data, primarily price and volume, to identify past trends and behaviour in tradeable market products. By understanding how these products have functioned in the past, technical traders attempt to forecast future price movements to enable traders to enter and exit trades at the right time in order to realise a profit. TA is based upon the following assumptions [45]:

- Market value is determined solely by the interaction of demand and supply.
- Although there are minor fluctuations in the market, stock prices tend to move in trends that persist for long periods of time.
- Shifts in demand and supply cause reversals in trends.
- Shifts in demand and supply could be detected in charts.
- Many chart patterns tend to repeat.

The points given above clearly indicate that TA is based upon the simple concept of supply and demand. The technical analyst is not interested in the reasoning behind a shift between supply and demand, but rather in the shift itself. An increase in a stock price is due to high demand or low supply, while a decrease in price is due to either low demand or high supply. Identification of supply and demand levels allows the technical analyst to position him or herself by timing a trade to make a profit. Technical analysis is concisely expressed by Prings [134] with the following statement:

"The technical approach to investment is essentially a reflection of the idea that prices move in trends which are determined by the changing attitudes of investors toward a variety of economic, monetary, political and psychological forces... Since the technical approach is based on the theory that the price is a reflection of mass psychology in action, it attempts to forecast future price movements on the assumption that crowd psychology moves between panic, fear, and pessimism on one hand and confidence, excessive optimism, and greed on the other."

2.3.2 Dow Theory

The father of TA is considered to be Charles Dow. His ideologies were developed in late 1800s and have been refined over the decades by so many others, defining current TA methods and referred to as the *Dow theory* [22][31]. Of the many theorems that Dow defined, three stand out:

- Price discounts everything. What this means is that all information, including supply and demand, is reflected by the price of the security. Price reflects the sum of all the knowledge of market participants and represents the fair value of the security.

- Price movements are not totally random. This theorem states that prices tend

to trend, and trends could be identified. The ability to apply TA to any period allows the identification of long-term as well as short-term trends. Three different types of trends exist, namely daily, secondary and primary trends. Daily trends includes movements that take place within a single trading day, secondary trends covers movements up to a month, and primary trends represent long-term price movements.

- The actual price of a security is more important than the reason why the security has reached a certain level. Focusing on the current price and its potential direction is what matters when it comes to TA. The reason why the price may rise or fall is unimportant.

2.3.3 Technical Analysis Controversy

Despite the century-long history of TA amongst investment professionals, it has often been viewed by academics and researchers with contempt. This is mainly due to the belief in the *efficient markets hypothesis* (EMH) developed by Fama in the 1960s [51, 52, 53]. EMH states that market prices follow a random walk, making it impossible to use past behaviour to make profitable predictions. The theory of EMH has been supported by Alexander [2], Jensen and Bennington [83], Dennis [42] and Malkiel [110]. One possible reason that may have contributed to the criticism of TA is that academic investigation of technical trading has not been consistent with how TA is exercised in practice [123]. The truth of the matter is that EMH is highly controversial and frequently debated.

The accumulation of financial literature indicating that the market is less efficient than was originally believed has revived the EMH topic in the academic world. Work produced by Lo and Mackinlay [108], Brock *et al.* [21], LeBaron [103] and Brown [22] have dismissed the theory of EMH. In the past decade, computational intelligence has also played a part in falsifying EMH and discovering exploitable patterns in security

prices. Genetic algorithms and genetic programming have been successfully applied together with TA to discover rules for the stock market [3, 14, 15, 122] and the foreign exchange market [41, 123, 124, 152]. Particle swarm optimisation algorithms are the latest paradigms to have been applied with TA [125, 126, 127, 151], producing noteworthy results.

TA in no way portrays itself as the *de facto* way of viewing a security, and does not result in flawless predictions. On the contrary, TA provides tools that allow an investor to view securities from a different viewpoint, contributing valuable information to a final decision that may increase the probability of realising a profit. The following books are recommended to the interested reader [13, 31, 45, 121]. Technical analysts use technical market indicators extensively. These are typically mathematical transformations of price and volume. Indicators are used to highlight security behaviour in order to determine security properties, such as trend, direction, supply and demand to name a few. Technical market indicators are further discussed in chapter 3.

2.4 Fundamental Analysis

A different analytical methodology used today in determining future stock price levels is *fundamental analysis* [70]. This involves analysis of the company's income statements, financial statements, management, company strategy, and generally any fundamental information on the company itself. Fundamental analysis focuses mainly on determining price movements within a primary trend and sometimes in secondary trends, making it suitable for long-term investments. Companies are generally valued based on all fundamental data and if a company is discovered to be under-valued or over-valued, company stocks are either bought or sold respectively. The stocks are held until a correction in the mispriced company takes place and a profit is realised. Table 2.4 lists the main difference between fundamental and technical analysis. Fun-

damental analysis is beyond the scope of this thesis, but has much to offer to improve models and predictions. In the future research section of chapter 7, a brief description is given of how it could be possible to include fundamental analysis to improve models.

Table 2.1: Fundamental vs. technical analysis

	Fundamental	**Technical**
Time horizon	Long-term investments	Short-term trading
Analysis focus	Financial statements	Historic prices
Analysis effort	Time consuming(manual)	Partially automated
Relative trade volume	Large	Small

2.5 Conclusion

This chapter served as a background to the financial aspect of this thesis. Stock trading topics were described, specifically the stock market, stock properties and stock market dynamics. A description on how profit could be realised via stock trading and the difficulties associated with this was laid out. Furthermore, this chapter presented technical analysis, an integral part of this study. Principles and theories on the topic were described, based on studies developed by Charles Dow in the late 1800s. The knowledge contained in this chapter is fundamental to understanding the work in the later chapters of this thesis.

Chapter 3

Technical Market Indicators

This chapter describes technical analysis methodology of technical market indicator tools. Section 3.1 defines technical market indicators, including the purpose of such indicators and how technical market indicators could be used to derive security related information. Sections 3.2 through section 3.4 presents the four indicators selected for the empirical part of this thesis, namely Aroon, Bollinger Bands, Relative Momentum Index and Moving Average Convergence/Divergence. In the section dedicated to each indicator, a description of the indicator is given, along with associated mathematical formulae, default parameter values, and derived trading rules.

3.1 Introduction

A *technical market indicator* (TMI) is defined as a time series that is derived from applying a mathematical formula to the price data of a specific security. The price data is broken down into periods, which can be based on intra-day, daily, weekly, monthly or yearly periods. For each period the open, high, low and close price is defined and used in the technical market indicators. In many cases the formula incorporates other information regarding the security, such as volume and volume

weighted average price (VWAP). TMI time series points extend from the past to the present and enable an analysis of price levels throughout time. The indicator exposes properties and behaviour that usually are not clear by inspecting the price alone. Such properties and behaviour provides a unique perspective on the strength and direction of the underlying security's future price.

Different indicators expose different properties and behaviour, such as supply, demand, momentum, volatility, volume, trend, sentiment and retracement. Using a single TMI may not yield satisfactory results. The chances of a single indicator producing sufficient information to enable a concrete trading decision is much smaller than the combination of indicators. Combining the effects of a number of indicators will yield more consistent results, with which more systematic trading decisions could be made. The different indicators chosen should be selected in a way that complement each other. There is no use combining the effect of two momentum or two trend indicators, since they both expose the exact same property. The combination of a trend and momentum indicator would be more beneficial.

TMIs are generally used for three reasons: prediction, confirmation and notification. More specifically:

- The direction of a security price can be predicted, together with the actual security price in some cases.
- Confirmation whether a security is in a bull or bear period.
- Indicators can notify traders whether a security is over-bought or over-sold.

Several TMIs exist, including: Aroon [24], Bollinger Bands [19], Chaikin Volatility [31], Directional Movement Index [162], Elder Ray [47], Momentum, Money Flow Index, Moving Average Convergence/Divergence [7], Parabolic Stop and Reverse [162], Percentage Bands [31], Relative Strength Index [162] and Triple Exponential Moving Average [31]. For the purposes of this thesis Aroon, Moving Average Con-

vergence/Divergence and Relative Strength Index are presented in this chapter. The reason why these four indicators were chosen is because of their popularity and that the time series they produce oscillate in a fixed range [31]. For a complete source of technical market indicators, the interested reader is referred to Colby's encyclopedia [31].

Each TMI presented consists of a set of parameters. These parameters are defined together with the default values commonly used. Such parameters could be altered in order to suit individual trader preference or specific security characteristics. A set of trading rules is presented for each TMI, which trading rules return one of the following actions in the set $\{BUY, SELL, CUT\}$. A BUY action entails buying the underlying security, while the $SELL$ action represents a short sell. The CUT action signals getting out of a position, either selling in the case a security that was bought or buying back in the case a security that was sold short.

3.2 Aroon

This section covers the Aroon indicator. A detailed description of the indicator is given together with associated mathematical formulae, default parameter values, and derived trading rules.

3.2.1 Description

The *Aroon* indicator was introduced by Chande in 1995 [24]. The indicator attempts to detect trend reversals and trend strengths quickly. It measures the number of time periods within a predefined time window since the most recent high price and low price. The main assumption this indicator makes is that a security's price closes at a high for the given period in an up-trend, and at a low for the given period in a down-trend.

3.2.2 Rules and Interpretation

The indicator is defined by the following equations:

$$AroonUp_p(t) = 100\left(\frac{HighIndex_p(t)}{p}\right) \tag{3.1}$$

$$HighIndex_p(t) = index(max\{price(j)\}_{j=t-p}^{t}) - t + p \tag{3.2}$$

$$AroonDown_p(t) = 100\left(\frac{LowIndex_p(t)}{p}\right) \tag{3.3}$$

$$LowIndex_p(t) = index(min\{price(j)\}_{j=t-p}^{t}) - t + p \tag{3.4}$$

where p is the size of the time window (a 14 day period is commonly used) [24], $HighIndex_p(t)$ the number of periods within p since the most recent highest observed price, and $LowIndex_p(t)$ is the number of periods within p since the most recent lowest observed price.

If a price makes a new n period high, $AroonUp_p(t)$ is equal to 100 indicating a strong price trend. When new highs are not made, the value of $AroonUp_p(t)$ weakens

to the point where it is equal to 0, indicating that the up-trend has lost bullish momentum. If a price makes a new n period low, $AroonDown_p(t)$ is equal to 100 indicating a weak price trend. If new lows are not made, the value of $AroonDown_p(t)$ weakens to the point where it is equal to 0, indicating that the down-trend has lost bearish momentum.

Referring to figure 3.1, an upper fixed level (L_{upper}) and a lower fixed level (L_{lower}) are plotted at 70 and 30 respectively on the chart. These plotted levels are used to aid the identification of strong up-trends or down-trends. If $AroonUp_p(t)$ remains in the bands between 100 and 70, while $AroonDown_p(t)$ remains in the bands between 30 and 0, then a strong up-trend is indicated. A strong down-trend is indicated when $AroonDown_p(t)$ remains in the bands between 100 and 70, while $AroonUp_p(t)$ remains in the bands between 30 and 0. Using the above mentioned observations, the following trading rules are defined:

- if $AroonUp_p(t) > L_{upper}$ and $(AroonDown_p(t) < L_{lower})$ then BUY
- if $AroonDown_p(t) > L_{upper}$ and $(AroonUp_p(t) < L_{lower})$ then $SELL$

When the $AroonUp_p$ and $AroonDown_p$ time series move together in parallel or roughly at the same level, then a period of consolidation is indicated. Further consolidation is expected until a directional move is indicated by an extreme level or a crossover of the two time series. If the $AroonUp_p$ time series crosses above the $AroonDown_p$ time series, potential strength is indicated and prices could be expected to begin trending higher. If the $AroonDown_p$ time series crosses above the $AroonUp_p$ time series, potential weakness is indicated and prices could be expected to begin trending lower. In the situation where there is a crossover of the two time series, the following CUT trading rules can be defined:

- if $AroonUp_p(t-1) < AroonDown_p(t-1)$ and $AroonUp_p(t) > AroonDown_p(t)$ then CUT

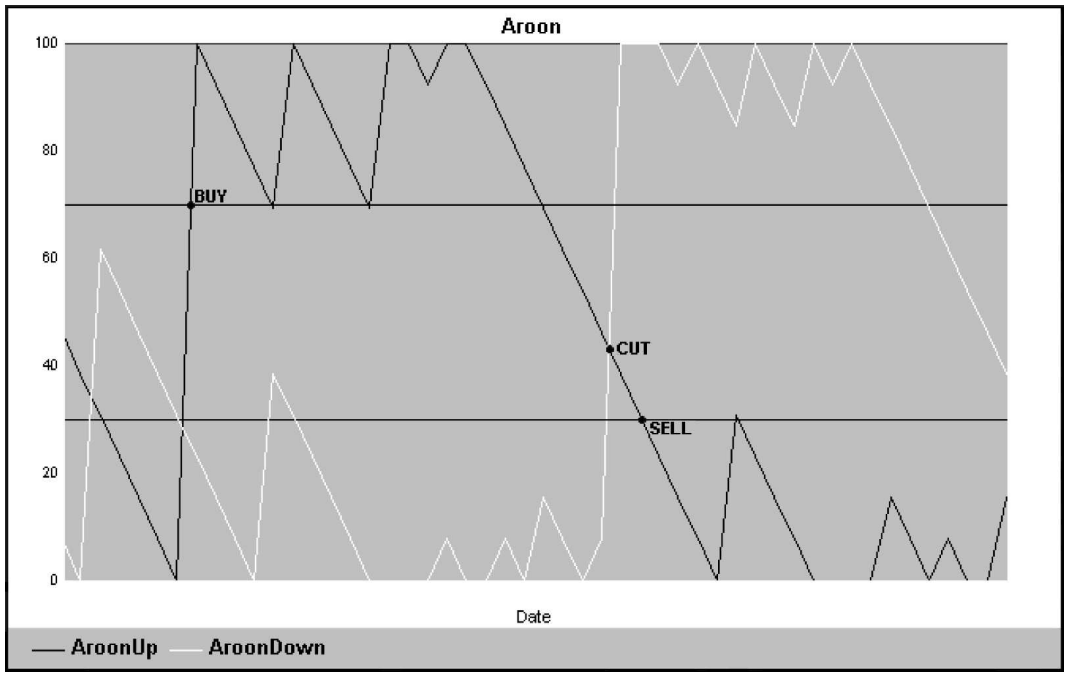


Figure 3.1: Aroon chart

- if $AroonUp_p(t-1) > AroonDown_p(t-1)$ and $AroonUp_p(t) < AroonDown_p(t)$ then CUT

Figure 3.1 illustrates the Aroon indicator, highlighting on the time series where the different trade actions are extracted based on the defined indicator rules.

3.3 Bollinger Bands

This section covers the Bollinger Bands indicator. A detailed description of the indicator is given together with associated mathematical formulae, default parameter values, and derived trading rules.

3.3.1 Description

The *Bollinger Bands* indicator was created by Bollinger in the early 1980s [19]. It addresses the issue of dynamic volatility by introducing adaptive bands that widen

during periods of high volatility and contract during periods of low volatility. The dynamic bands used by this indicator are an advantage over similar indicators that use static bands, and which are hence less responsive to volatile markets. The main purpose of Bollinger Bands is to place the current price of a security into perspective, providing a relative definition of high and low volatility (therefore supply/demand) and trend. Bollinger suggests this indicator should be used in conjunction with the Relative Strength Index or Money Flow Index indicators.

3.3.2 Rules and Interpretation

There are three time series that compose the Bollinger Bands indicator, which consists of an upper ($UpBand_p$), middle ($MidBand_p$) and lower time series ($LowBand_p$). $MidBand_p$ is usually a simple moving average, used as a measure of intermediate-term trend. $UpBand_p$ and $LowBand_p$ are standard deviations of $MidBand_p$, adjusted by a constant value above and below $MidBand_p$. The three time series are defined as:

$$MidBand_p(t) = \frac{\sum_{j=t-p+1}^{t} price(j)}{p} \tag{3.5}$$

$$LowBand_p(t) = MidBand_p(t) - \left[D\sqrt{\frac{\sum_{j=t-p+1}^{t}(price(j) - MidBand_p(t))^2}{p}} \right] \tag{3.6}$$

$$UpBand_p(t) = MidBand_p(t)) + \left[D\sqrt{\frac{\sum_{j=t-p+1}^{t}(price(j) - MidBand_p(t))^2}{p}} \right] \tag{3.7}$$

where $price(j)$ represents the price of the security (commonly the closing price is used), p is the number of periods used for the simple moving average calculations, and the constant D is an adjustment value by which the standard deviation of the simple moving average is shifted above and below $MidBand_p$. The default variable values used by Bollinger are 20 for the period p and 2.0 for the adjustment factor D [19].

Bollinger determined that simple moving averages of less than 10 periods are not effective. A straightforward methodology that can be employed to determine the effectiveness of p is to investigate the number of times that the bands are penetrated. Frequently penetrated bands suggest that a larger p should be used, while prices that rarely penetrate the outer bounds suggest a smaller p. Strictly speaking, the following effect is desirable, which highlights suitable parameters: after each high where $UpBand_p(t)$ is penetrated only once, a low follows which penetrates $LowBand_p(t)$ only once and vice versa. If a number of highs penetrate $UpBand_p(t)$ multiple times in sequence or a number of lows penetrate $LowBand_p(t)$ multiple times in sequence, a larger p value is required. It is important to note that even with suitable parameters the upper band and lower band may be penetrated multiply in sequence from time to time.

The price of a security is drawn in relation to the three bands. If the price of the security is close to the upper band, it is considered to be a relatively high price while a security price closer to the lower band is considered to be a relatively low price. A time series referred to as percentage bands ($\%b$) is calculated to quantify the relative price of the security over time, defined as:

$$\%b(t) = 100\left(\frac{price(t) - LowBand_p(t)}{UpBand_p(t) - LowBand_p(t)}\right) \tag{3.8}$$

$\%b$ values close to 100 indicate prices that are at relatively high levels, possibly unsustainable, and an indication of a bearish reaction to follow. $\%b$ values close to 0 indicate the exact opposite, namely relatively low price levels, possibly unsustainable, and an indication of a bullish reaction to follow. The bearish or bullish action is confirmed when $\%b$ penetrates the level set at 50. A multiple price penetration of $UpBand_p$ indicates the security is over-bought while multiple price penetrations of $LowBand_p$ indicates the security is over-sold, amplifying the chances of a bullish or bearish reaction respectively. The following trading rules are defined based on the above-mentioned observations:

- if $\%b(t-1) < 0$ and $\%b(t) > 0$ then BUY
- if $\%b(t-1) > 100$ and $\%b(t) < 100$ then $SELL$
- if $\%b(t-1) < 50$ and $\%b(t) > 50$ then CUT
- if $\%b(t-1) > 50$ and $\%b(t) < 50$ then CUT

Figure 3.2 illustrates the $\%b$ time series and is labeled with associated trade actions based on the defined trade rule.

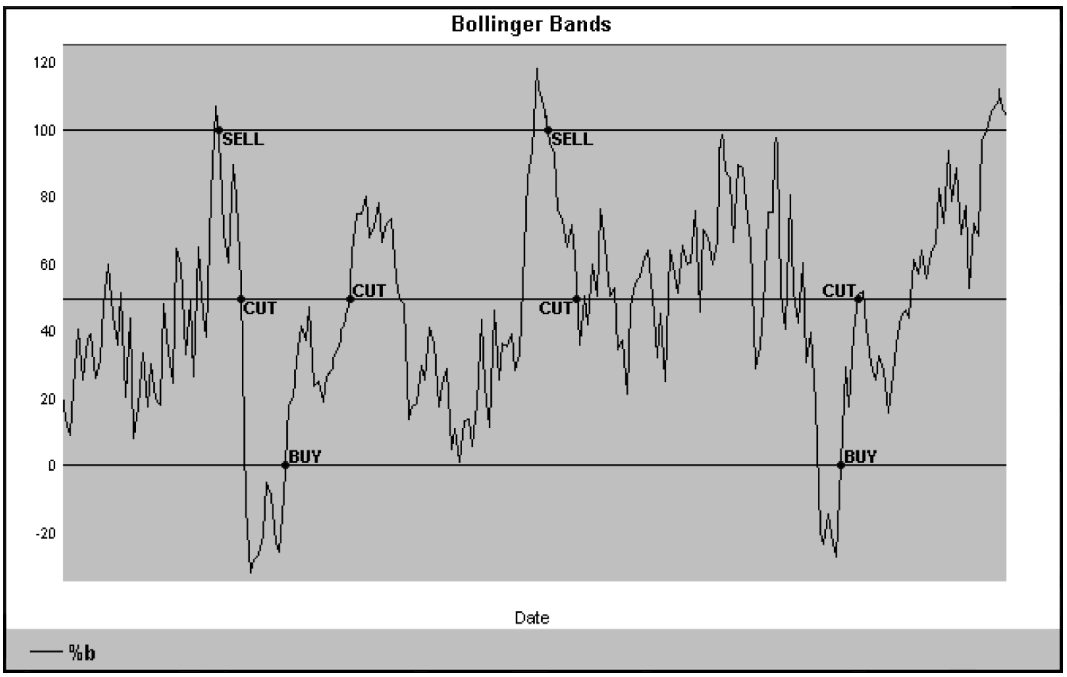


Figure 3.2: Bollinger Bands chart

The interval between the $UpBand_p$ and $LowBand_p$ time series highlights the volatility of the security. The further the two bands are apart, the more volatile the security is considered to be, while a less volatile security results in the two bands being closer to each other. The following time series can be calculated to quantify this effect over time:

$$bandwidth(t) = \frac{UpBand_p(t) - LowBand_p(t)}{MidBand_p(t)} \tag{3.9}$$

Since the value $bandwidth(t)$ quantifies the volatility of the security at time t, $bandwidth(t)$ can be used to identify and understand changes in supply and demand for the underlying security.

3.4 Moving Average Convergence/Divergence

This section covers the Moving Average Convergence/Divergence indicator. A detailed description of the indicator is given together with associated mathematical formulae, default parameter values, and derived trading rules.

3.4.1 Description

The *Moving Average Convergence/Divergence* (MACD) indicator was developed by Appel in 1979 [7] as a stock market timing device, utilising market momentum and trend. MACD has proved to be best used in trending markets rather than choppy non-trending markets. It is more efficient for longer term primary trends rather than daily or secondary trends.

3.4.2 Rules and Interpretation

A short and long period exponential moving average (EMA) is calculated on the security price. The difference between the two values is referred to as the price momentum. A second time series is calculated by applying another EMA on the price momentum using a smaller period than the ones originally used on the security price. These two time series formulate the MACD indicator, defined as:

$$PriceMomentum(t) = EMA_a(price) - EMA_b(price) \tag{3.10}$$

$$MomentumTrigger(t) = EMA_c(PriceMomentum) \tag{3.11}$$

$$EMA_p(t) = price(t)\left(\frac{2}{p+1}\right) + \frac{\sum_{j=t-p+1}^{t} price(j)}{p}\left(100 - \frac{2}{p+1}\right) \tag{3.12}$$

where a,b and c indicate the periods to be used for the exponential moving average calculations, where $b > a > c$. Appel recommended using a 12 day period for the fast exponential moving average and a 26 period for the slow exponential moving average to calculate the price momentum. A 9 day period was used for the exponential moving average in the $MomentumTrigger$ time series [7]. The short period EMA time series will be referred to as the fast EMA, since it reacts quicker to price movements compared to the second EMA time series. For the same reason, the large period EMA will be referred to as the slow EMA.

The $PriceMomentum$ time series oscillates around the zero axis, highlighting positive and negative market momentum. Positive momentum indicates that the average price for the fast EMA exceeds that of the slow EMA, highlighting a rise in the underlying price. In this case the security is over-bought, highlighting a bullish period. Negative momentum indicates a bearish period because the fast EMA has fallen below that of the slow EMA, which highlights that the security is over-sold, leading to a fall in the security price. The direction of the price momentum is also used to indicate the strength of a bullish/bearish trend. A negative price momentum with a negative gradient indicates a strong bearish period and a period where it would possibly be a bad time to buy. A positive price momentum having a positive gradient indicates that there is a strong bullish trend. When the price momentum shifts from a positive to a negative value or vice versa, a trend reversal is indicated which is used to generate a CUT action. The following trade rules are defined for MACD:

- if $PriceMomentum(t-1) < 0$ and $PriceMomentum(t) > 0$ then CUT
- if $PriceMomentum(t-1) > 0$ and $PriceMomentum(t) < 0$ then CUT

The $MomentumTrigger$ time series in combination with the $PriceMomentum$ time series provides the necessary information required to enable trade entry. The trading actions are returned when there is a crossover of these two time series in the

following way:

- if $PriceMomentum(t-1) < MomentumTrigger(t-1)$ and $PriceMomentum(t) > MomentumTrigger(t)$ then BUY
- if $PriceMomentum(t-1) > MomentumTrigger(t-1)$ and $PriceMomentum(t) < MomentumTrigger(t)$ then $SELL$

These actions enable the exploitation of short-term trends to realise profits. The short-term trends may be up-trends or down-trends during periods of positive or negative price momentum. Figure 3.3 illustrates the MACD indicator, with the trade rules applied on the time series and all trade actions labelled.

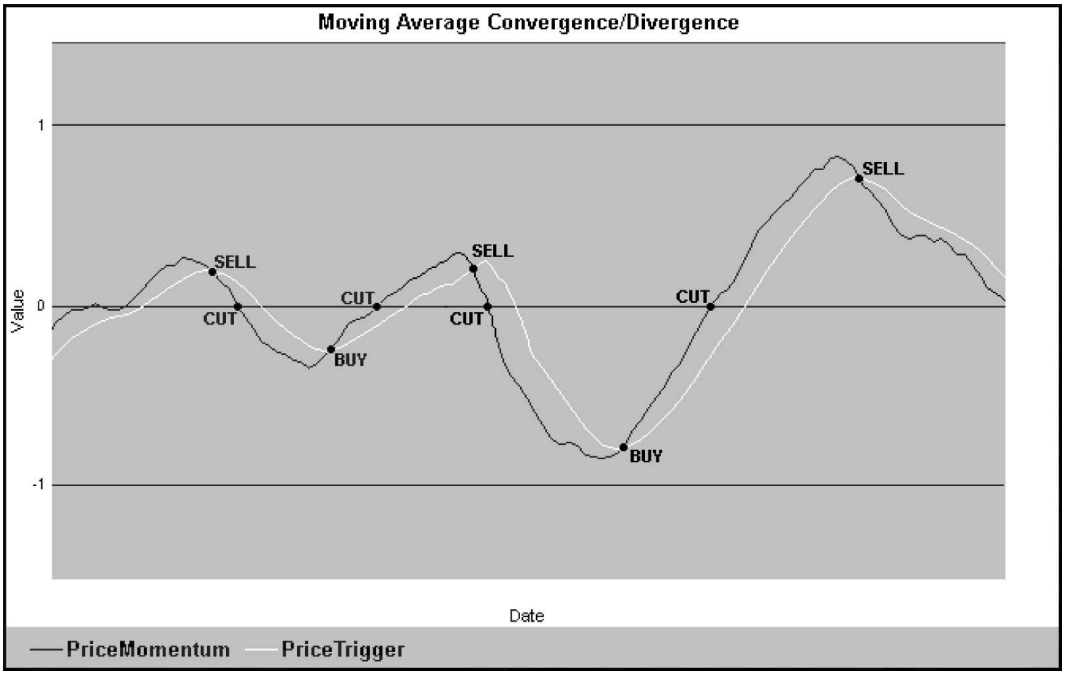


Figure 3.3: MACD chart

Additional information is extracted from $PriceMomentum(t)$ when the direction of movement of the security price diverges from the direction of movement of the price momentum. A bullish period is indicated when there is positive divergence in the case where the security price is falling while $PriceMomentum(t)$ is in an up-

trend. A bearish period is indicated in the case of negative divergence where the security price is rising while $PriceMomentum(t)$ is in a down-trend.

3.5 Relative Strength Index

This section covers the Relative Strength Index. A detailed description of the indicator is given together with associated mathematical formulae, default parameter values, and derived trading rules.

3.5.1 Description

The *Relative Strength Index* (RSI) was introduced by Wilder in 1978 [162]. RSI returns a value that continuously oscillates, tracking price strength and ultimately displaying the velocity and momentum of a security price. This is done by comparing the magnitude of a security's recent gains to the magnitude of its recent losses.

3.5.2 Rules and Interpretation

RSI is calculated using:

$$RSI_p(t) = 100\left(1 - \frac{1}{1 + RS_p(t)}\right) \tag{3.13}$$

$$RS_p(t) = \frac{TotalGain_p(t)}{TotalLoss_p(t)} \tag{3.14}$$

$$TotalGain_p(t) = \sum_{j=t-p+1}^{t} (price(j) - price(j-1) > 0) \tag{3.15}$$

$$TotalLoss_p(t) = \left| \sum_{j=t-p+1}^{t} (price(j) - price(j-1) < 0) \right| \tag{3.16}$$

Note that if $average_{loss} = 0$, then $RSI = 100$ by definition.

In the above p is the number of periods used for calculating $average_{loss}$ and $average_{gain}$. A default value of 14 was used by Wilder [162]. Larger values for p

result in smoother RSI curves, while small values for p result in large volatility in the curve.

Two fixed levels need to be defined to aid the interpretation of RSI, namely an upper level (L_{upper}) and a lower level (L_{lower}). Wilder recommended the upper level to be set at 70 and the lower level to be set at 30. When RSI is above the upper level and then falls below the upper level, this is considered as a warning of a potential trend reversal, meaning that a bearish reaction of the underlying security is to be expected. Alternatively, a bullish reaction is expected when RSI is below the lower and then rises above the lower level. These two levels also represent over-bought and over-sold levels respectively.

A mid level (L_{mid}) for RSI is at 50, which can also be used to further interpret RSI. Values above 50 indicate that average gains are more than average losses, which can be used as a confirmation of a bullish trend. Bearish trends can be confirmed when RSI falls below 50, since the average losses are more than the average gains.

The following RSI trading rules are defined given the behaviour of the RSI time series:

- if $RSI(t-1) < L_{lower}$ and $RSI(t) > L_{lower}$ then BUY
- if $RSI(t-1) > L_{upper}$ and $RSI(t) < L_{upper}$ then $SELL$
- if $RSI(t-1) < L_{mid}$ and $RSI(t) > L_{mid}$ then CUT
- if $RSI(t-1) > L_{mid}$ and $RSI(t) < L_{mid}$ then CUT

Refer to figure 3.4 for an illustration of the RSI time series, with all trade actions indicated based on the defined rules.

BUY and $SELL$ actions could also be returned by looking for positive and negative divergences between RSI values and the underlying security. A *divergence* takes place when a new high or a new low takes place in the price and RSI fails to

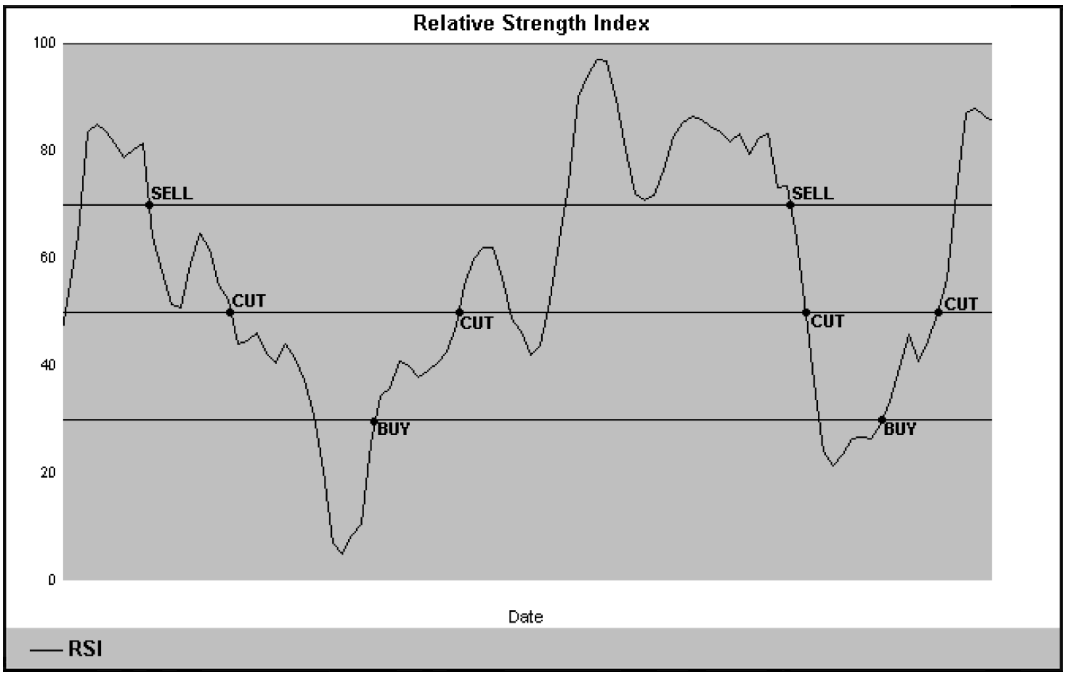


Figure 3.4: Relative Strength Index chart

exceed its previous high or low respectively. Usually, divergences that occur after an over-bought or over-sold security can be used to define more reliable rules. A negative divergence during a period where the security is over-bought would entail a $SELL$ action while a BUY action would be returned when a positive divergence takes place during a period where the underlying security is over-sold. It is said that a "failure swing" is completed when the RSI value turns and falls below its last low, or rises higher than its last high, thus confirming a reversal.

3.6 Conclusion

This chapter covered the technical market indicators that form the technical analysis tools of choice to be used in this study. Four technical market indicators were presented together with corresponding mathematical formulae, default parameters and derived trading rules. The indicators selected were Aroon, Bollinger Bands, Relative Momentum Index and Moving Average Convergence/Divergence: these indicators

are used in the remainder of this thesis.

Chapter 4

Computational Intelligence Paradigms

The work in this thesis involves a number of *computational intelligence* (CI) paradigms, which are covered in this chapter. Three main CI paradigms are presented, namely artificial neural networks, particle swarm optimisation and co-evolution. Section 4.1 focuses on artificial neural networks, presenting artificial neurons, activation functions and architectures. Neural network learning approaches are presented in section 4.1.5. A brief introduction to evolutionary computation is made in section 4.2. Particle swarm optimisation is covered in section 4.3, presenting neighbourhood topologies, the PSO algorithm and a discussion on various PSO related parameters. Co-evolution is covered in section 4.4. Two types of co-evolution are described, namely competitive and cooperative co-evolution. The work produced in this study focuses on competitive co-evolution, which is discussed in more detail in section 4.4.2. Other co-evolution related topics that are covered include competitive fitness, fitness evaluation, fitness sampling and the hall of fame. Relevant applications for each paradigm are provided, highlighting financial applications that are related to this study.

4.1 Artificial Neural Networks

This section explains artificial neural networks (ANN). The section briefly describes the human brain and how ANNs were inspired by modelling the brain. The structure and functionality of ANNs are explained together with different learning approaches applicable to ANNs.

4.1.1 The Human Brain

The human brain consists of nerve cells called *neurons* that form connections with one another, called *synapses*. These neurons form countless modules of networks that are extremely complex. It is estimated that these networks contain more than one hundred billion neurons for an adult brain and trillions of synapses [43], capable of emitting electrical and chemical signals. It is the firing of these signals throughout the neural complexity of the brain that allows intelligent behaviour. The human brain is undoubtedly the most complex and advanced processor in the world today, able to process in a non-linear parallel manner. The brain can process visual, acoustic and sensory information immaculately, but this only partly describes its abilities - and not even this functionality has been reproduced with today's advanced technology. Replicating the human brain is an inconceivable task today and it will take decades of technological advancements for humanity to come anywhere close to such an effort. The following books are recommended to the interested reader on neural networks [16, 111].

4.1.2 Artificial Neurons

The *artificial neural network* (ANN) was inspired by studies of the human brain and attempts to model its functionality. The *artificial neuron* (AN) forms the smallest functional component of the ANN, similar to the biological neurons in the brain. Each AN receives signals, either from other ANs, or the environment, and emits an

output signal by combining all the received signals. Each connection has a weight value associated to it, which determines the strength of received signals. Each neuron utilises a mathematical function that allows received signals to be transformed into a single signal, which is emitted. These functions are referred to as an *activation function*. Figure 4.1 illustrates the structure of an AN.

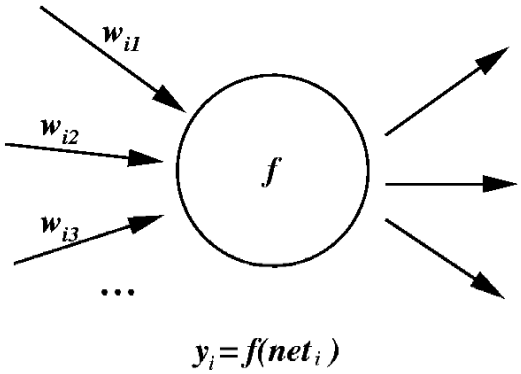


Figure 4.1: Artificial neuron

4.1.3 Activation Functions

Figure 4.2 illustrates four commonly used activation functions. As mentioned previously and shown by figure 4.1, the input into an activation function is an aggregate of all signals received in different strengths. These strengths are determined by weights that are associated with the connecting neurons. The formula for each of the illustrated activation functions is given as:

(a) Linear function (figure 4.2(a)):

$$F(\tau) = \beta\tau \tag{4.1}$$

(b) Sigmoid function (figure 4.2(b)):

$$F(\tau) = \frac{1}{1 + e^{-\lambda\tau}} \tag{4.2}$$

(c) Hyperbolic tangent function (figure 4.2(c)):

$$F(\tau) = \frac{2}{1 + e^{-\lambda\tau}} - 1 \tag{4.3}$$

(d) Gaussian function (figure 4.2(d)):

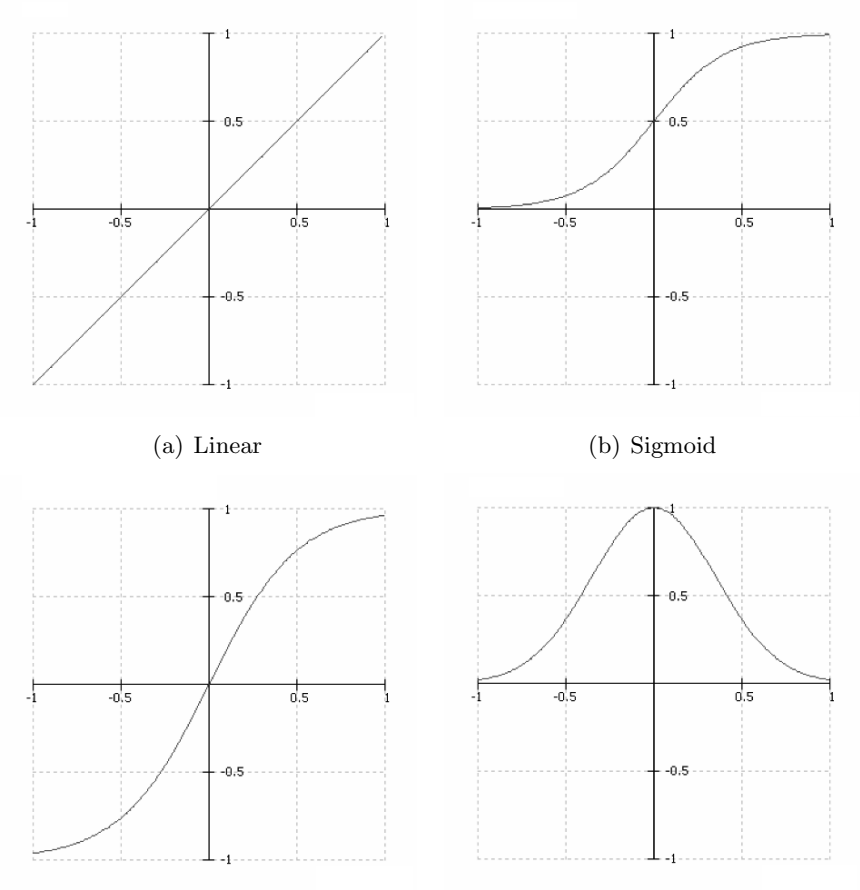
$$F(\mu) = e^{-\mu^2/\sigma^2} \tag{4.4}$$

where τ defines the net inputs, β is a constant defining the gradient of the linear function, λ defines the steepness of the sigmoid and hyperbolic functions, σ^2 defines the variance of the Gaussian distribution and μ the mean.

4.1.4 Architecture

A single AN is capable of learning simple linearly separable functions [49] and forms the smallest structural component of an ANN. An AN exhibits relatively simple behaviour when it functions on its own. A structure capable of learning highly complex non-linearly separable functions can be constructed by combining a number of neurons together. An ANN is traditionally structured in three layers of neurons, consisting of input, hidden and output neurons, all of which are fully interconnected. This type of ANN is the most straightforward in its structure and is referred to as a *feed forward neural network* (FFNN).

The complexity of the network may be increased by adding neurons to a layer or with the connection of neurons between adjacent layers. It has been proven that only one hidden layer containing sufficient number of neurons can approximate any given continuous function [18, 78, 79, 84]. Additionally, complexity may be increased by connecting neurons that do not belong to adjacent layers. For the purpose of this study, a standard FFNN is used.



(a) Linear (b) Sigmoid

(c) Hyperbolic tangent (d) Gaussian

Figure 4.2: Activation functions

Signals are presented to the input layer of the ANN and the signals are passed on to connected ANs. The propagation of signals through each layer of the ANN results in an output signal from each AN in the output layer. When a vector of inputs is presented describing a specific state, the NN produces an answer described by its outputs. An ANN can be seen as a nonlinear function that aims to map a set of inputs to a set of outputs. Figure 4.3 illustrates the structure of a traditional ANN.

Special care always needs to be taken to avoid *overfitting* during the training of an ANN. Overfitting may occur when the ANN structure is oversized, there is noise in the training data or when an ANN is trained for too long. Overfitting implies that the ANN structure contains excess degrees of freedom, allowing noisy data to

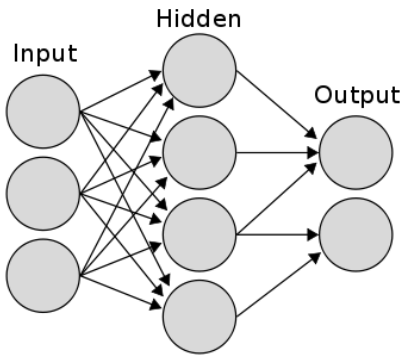


Figure 4.3: Artificial neural network

be memorised by the structure. This results in favourable outputs produced for data patterns on which the ANN has been trained with, and less favourable outputs produced for newly introduced inputs not included in the training process [49]. Different methods have been developed to aid architecture optimization, which include pruning and growing. Pruning is a method that removes neurons that have an unfavourable effect on the learning abilities of the ANN [48, 105, 119]. Pruning involves starting with a large ANN and then removing redundant and irrelevant weights, hidden units and output units. Growing is a different approach to architecture selection, where a small ANN structure is created that contains a minimal number of ANs, then methodically adds ANs to the structure [65, 74, 80, 100]. More work has been done on the issues of generalisation and overfitting by Amari *et al.* [4] and Müller *et al.* [120]. In general, overfitting can be avoided by separating the input and expected output patterns into two disjointed sets, namely an in-sample set and an out-sample set. The ANN is trained using the in-sample set, while its predictive quality is measured against the out-sample set. An ANN is then selected by choosing a set-up where it performs satisfactorily on both sets, indicating that the ANN has learnt all patterns that have been presented during training and it has the ability to generalise over the patterns that were not used whilst training.

4.1.5 Learning Approaches

An ANN does not possess any adaptive behaviour on its own, but its practicality comes into play through the use of various algorithms designed to alter and adjust the weights of the connections throughout the network. The process of adjusting weight values is referred to as *artificial neural network learning*. Three major learning paradigms exist which are described below:

- **Supervised learning**: This type of learning requires prior knowledge of the problem domain. Supervised learning requires a training set of data patterns consisting of inputs and target outputs. Supervised learning adjusts the weights of the ANN such that the error between expected output and actual ANN output is minimised. This type of learning is mostly done via *gradient descent* optimisation (GD). A well-known and widely used GD algorithm was developed by Werbos [160]. The algorithm developed by Werbos utilises *backpropagation*, which propagates an error signal from the output layer through to the input layer, adjusting weights accordingly. Other learning algorithms relevant to this category includes generalised delta [112], Widrow-Hoff [23], scaled conjugate gradient learning rules [118] and particle swarm optimisation [44, 71, 73, 81, 93, 115, 139, 158]. This learning paradigm is applicable to pattern recognition, regression and classification problems [16, 104].

- **Unsupervised learning**: This type of learning only requires a vector of inputs, but not any associated desired outputs. In general, this learning paradigm attempts to discover patterns and features without any external help. Applications related to unsupervised learning in general include clustering [97], classification [109, 33] and compression [32]. Kohonens' *self-organising maps* and *learning vector quantizer* (LVQ) [97] falls within this category. The latest unsupervised neural network learning technique is that with the use of particle

swarm optimisation [63, 116, 128], which is the form of learning used in this study.

- **Reinforcement learning**: In this paradigm an actual data set consisting of inputs and outputs does not exist for learning purposes. The ANN interacts with its environment and based on its performance, the ANN is awarded or penalised. Awards and penalties are represented by positive or negative signals that adjust the weights of the ANN. Over time the network adapts and eventually produces outputs that are favourable. This learning type is applicable to sequential decision-making tasks and control related problems in general. LVQ-II by Kohonen [97] and Q-Learning by Watkins [159] are two popular reinforcement learning algorithms.

4.1.6 Artificial Neural Network Applications

ANNs have extensively been applied in a wide range of real-world problems. This includes the fields of medicine [96, 107], data mining [33, 109], data compression [40, 54], pattern recognition [32, 101, 104], gaming [25, 63, 128, 149] and robotics [57, 106]. Out of all computational intelligence paradigms, ANNs have played the most important role in the field of finance, with numerous applications in trading bonds [119], foreign exchange [164] and stocks [46, 102, 165]. ANN trading applications take into consideration market information with the objective of determining price direction in order to carry highly profitable trades at minimum risk. Stock trading applications in particular are relevant to the work in this thesis. With regards to neural networks in the financial sector, the following books are recommended [39, 114, 142, 146, 166].

4.2 Evolutionary Computation

Evolutionary computation (EC) is a paradigm within computation intelligence where population-based metaheuristic optimisation techniques are used. EC was inspired by Darwinian evolution, described as early as 1859 [36]. Mechanisms such as reproduction, mutation and elitism are frequently used in EC, highlighting concepts of evolutionary biology as the driving force behind such techniques. Barricelli [12] and Fraser [64] were the first in the 1950s to develop and apply EC. Other work followed by Schwefel [141], Holland [75, 76], Fogel [59, 60, 61] and Rechenberg [135]. All aforementioned work introduced a form of evolutionary computation completely disjointedly, which today forms the basis upon which EC is built. With regards to evolutionary computation, the interested reader is prompted to the following work by Back [9, 10]. EC algorithms include genetic algorithms (GA) [64, 68, 75, 76], genetic programming (GP) by Koza [99], evolutionary strategies [135, 141], evolutionary programming by Fogel [59, 60, 61], cultural evolution by Reynolds [136] and co-evolution which is extensively covered in section 4.4.

EC is implemented as a simulation in which a population of solutions to a specific problem is continuously evolved and improved over time. Solutions in an EC context are referred to as *chromosomes*. A fitness function is defined which possibly forms the most important component of EC. The fitness function maps a chromosome to a scalar value that represents the quality of a solution. The ability to determine and compare the quality of solutions is essential to *elitism*, which is an operation that allows the preservation of the best solutions within a population. Another important operation of EC is that of *reproduction*. Reproduction allows the combination of two or more solutions to form new solutions. The original solutions are referred to as parents while newer solutions are referred to as offspring. The process of combining the parents is called *crossover*. Offspring solutions are often randomly *mutated*, which allows the maintenance of diversity within a population to avoid premature

convergence. Usually the mutation is larger at the beginning of the algorithm to allow a global exploration of the search space and decreases over time to focus the exploration more locally on specific solutions [49]. The quality of the offspring is dependent on the selection of the parents, which is an extensively studied topic [49, 55, 69]. Algorithm 1 provides pseudo-code for an EC algorithm. Each iteration of the algorithm is referred to as a *generation*.

Algorithm 1 General Evolutionary Algorithm

1. Generate a population of p random solutions.
2. While no convergence:
   a) Evaluate each solution in the population using the fitness function.
   b) Use elitism to select e best solutions and preserve them unchanged.
   c) Produce p-e new solutions via reproduction and randomly mutate them.
   d) Create a new population by grouping the elitism and reproduction solutions together.

Convergence is reached in the following cases:

- the maximum number of generations is reached,
- the average or maximum fitness value does not change significantly over a certain number of generations, or
- an acceptable solution has been evolved that returns a satisfactory fitness.

There are multiple applications of GA and GP in the financial sector. Interested readers are referred to [28]. Financial applications more relevant to technical trading include foreign exchange trading [41, 124, 123, 152] and stock market trading [3, 14, 15, 122].

4.3 Particle Swarm Optimisation

This section discusses the basic particle swarm optimisation algorithm. The dynamics, different topologies and parameters relevant to the algorithm are covered. The section ends with some existing PSO applications in the financial world.

4.3.1 PSO Dynamics

Particle swarm optimisation (PSO) is a population based optimisation approach, introduced by Kennedy and Eberhart [91, 92]. A PSO consists of a swarm of particles, where each particle represents a potential solution. It aims to model the social behaviour of a flock of birds, where the particles within the swarm can "fly" within a multi-dimensional search space in a methodical and organised manner. The position of each particle is determined according to the experience of the particle itself and neighbouring particles. The particle position is updated using the following equation:

$$\vec{x}_i(t) = \vec{x}_i(t-1) + \vec{v}_i(t) \tag{4.5}$$

where $\vec{x}_i(t)$ is the position of particle i at time step t and $\vec{v}_i(t)$ is the velocity vector of particle i at time step t.

The velocity vector, $\vec{v}_i$, dictates the velocity and direction of the particle that drives the optimisation process. Based on the velocity, each particle moves towards the direction of its personal best position, $\vec{y}_i$, and the neighbourhood best position, $\vec{z}_i$. The new position of the particle is additionally influenced by two acceleration coefficients, which are used to scale up or down the influence of the personal best and neighbourhood best position. The factor associated to the personal best position is called the *cognitive factor*, while the one associated to the neighbourhood best is called the *social factor*. The following equation is used to update the particle velocity:

$$\vec{v}_i(t) = w\vec{v}_i(t-1) + \vec{\rho_1}(\vec{y}_i - \vec{x}_i(t)) + \vec{\rho_2}(\vec{z}_i - \vec{x}_i(t)) \tag{4.6}$$

$$\overrightarrow{\rho_1} = c_1\overrightarrow{r_1} \tag{4.7}$$

$$\overrightarrow{\rho_2} = c_2\overrightarrow{r_2} \tag{4.8}$$

where w is an inertia weight, $\overrightarrow{\rho_1}$ is the cognitive factor, $\overrightarrow{\rho_2}$ is the social factor. c_1 and c_2 are positive acceleration constants used to scale the contribution of the cognitive and social components respectively. r_1 , r_2 are random values in the range [0,1], sampled from a uniform distribution. These random values introduce a stochastic element to the algorithm. More detail on these are discussed in section 4.3.3.

A fitness function, f, needs to be defined to map the particle position vector into a scalar value. This will allow the evaluation of the particle quality that will help find the personal and neighbourhood best solutions. Pseudocode for a PSO is given in algorithm 2. The following references [29, 50, 94, 157] provide extensive information on PSO.

4.3.2 PSO Topologies

In the context of a PSO, a population of solutions is referred to as a *swarm* and the individual solutions in the swarm as *particles*. Each particle within the swarm attempts to discover the optimal solution by moving in different directions. The position of a particle at any point in time is influenced by the position of its own best solution (personal best) and the position of the best solution of all other particles with which it exchanges knowledge (neighbourhood best). The social structure that determines which particles share knowledge within a swarm is referred to as a *neighbourhood topology*. Different social network structures can be formed, with the following three topologies commonly used:

- **Star topology**: All particles exchange information with each other, forming a single but fully interconnected social network. With this topology all particle movements are affected by their own personal best solution and a global best

Algorithm 2 PSO

1. Initialise each particle in the swarm at a random position $\overrightarrow{x}_i$ within the search space.
2. Initialise each particle velocity vector $\overrightarrow{v}_i$ to zero.
3. Initialise each particle's personal best position $\overrightarrow{y}_i$ to its current position.
4. Repeat the following steps, t representing the current time step, while no convergence:
   a) Update each particle's fitness using a fitness function f.
   b) Update each particle's personal best position $\overrightarrow{y}_i$:
   if $f(\overrightarrow{x}_i(t)) > f(\overrightarrow{y}_i(t))$ then $\overrightarrow{y}_i(t) = \overrightarrow{x}_i(t)$
   c) Update the neighbourhood best position $\overrightarrow{z}_i$ for each particle:
   if $f(\overrightarrow{y}_i(t)) > f(\overrightarrow{z}_i(t))$ then $\overrightarrow{z}_i(t) = \overrightarrow{y}_i(t)$
   d) Update the position of each particle $\overrightarrow{x}_i$ in the swarm using equation 4.5.
   e) Update the velocity $\overrightarrow{v}_i$ of each particle in the swarm using equation 4.6.
5. Assuming that a maximisation of fitness is performed, return the best solution defined by $maxf(\overrightarrow{z}_i)$ of the entire swarm.

Convergence is reached in the following cases:

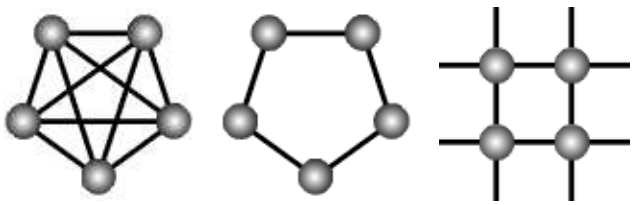
- the maximum number of iterations is reached,
- the average or maximum fitness value does not change significantly over a certain number of iterations, or
- an acceptable solution has been discovered that returns a satisfactory fitness.

solution. The global best solution forms the best solution of the entire swarm. The first PSO algorithm developed used the star topology and was referred to as the *GBEST* PSO. This is the simplest of topologies and has been shown empirically to tend to premature convergence on a stationary point [44, 157]. The star topology is illustrated in figure 4.4(a).

- **Ring topology**: A neighbourhood size is defined for this topology, which deter-

mines the number of particles with which each particle can exchange and share information with. If a neighbourhood size is 3, for example, neighbourhoods of 3 particles are formed by selecting a neighbour to the immediate left and right of each particle. With this topology, all particle movements are affected by their own personal best solution and the neighbourhood best solution. The algorithm that uses this topology is referred to as the *LBEST* PSO. It has been empirically shown that the LBEST PSO algorithm is less vulnerable in locating local minima and converges at a slower rate than the GBEST PSO, due to the increased search space that LBEST PSO explores [44, 89, 93, 145]. The ring topology is illustrated in figure 4.4(b).

- **Von Neumann**: Particles are arranged in a lattice using this topology, where each particle is connected with its immediate top, bottom, left and right particles [95]. The Von Neumann topology is illustrated in figure 4.4(a).



(a) Star (b) Ring (c) Von Neumann

Figure 4.4: PSO topologies

Other variations of social networks exist, such as spatial social networks [147], fitness-based spatial neighbourhoods [20], growing neighbourhoods [147], small-world social networks [89, 95], hypercube structures [1] and hierarchical social networks [82].

Depending on the problem domain, a favourable network structure should be selected that will enable the search space to be optimally explored. PSO topologies have been extensively researched [89, 90, 147, 157].

4.3.3 PSO Parameters

The inertia weight, w, was introduced by Shi and Eberhart [143] to control the exploration abilities of the swarm. The inertia weight is a means to control the step size within the search space that is to be explored. Large values of w facilitate more exploration, while smaller values focus the search on smaller regions of the search space. The ability to focus the search locally or globally via the inertia weight was followed by a natural extension of the static value to allow dynamic values [144]. An initial large value of w is used, which reduces over time. This allows an initial exploration that focuses on smaller regions around possible solutions as the search process progresses.

The cognitive and social components, as defined in equations 4.7 and 4.8, additionally influence the exploration abilities of the PSO algorithm. c_1 and c_2 are positive acceleration constants used to scale the contribution of the cognitive and social components respectively. r_1 , r_2 are random values in the range [0,1], sampled from a uniform distribution. These random values introduce a stochastic element to the algorithm. To avoid velocities and positions exploding towards infinite values, Kennedy has suggested maintaining the following relationship [88]:

$$c_1 + c_2 \leq 4 \tag{4.9}$$

Large values of c_1 will steer the particle more towards the direction of the personal best position, while larger c_2 values would cause the particle to be steered more towards the neighbourhood best position.

Convergence can be ensured by maintaining a relation combing the parameters w, c_1 and c_2. The relation was defined by Van den Bergh through theoretical and empirical analysis of the algorithms' convergent behaviour [157]:

$$w > \frac{1}{2}(c_1 + c_2) - 1 \tag{4.10}$$

with $w \leq 1$.

The topic of PSO convergence and analysis on the general properties of particle exploration of a problem domain is an ongoing topic of research [30, 157].

4.3.4 PSO Applications

PSO has been successfully applied to train supervised and unsupervised neural networks. Each particle represents a neural network weight vector with the PSO attempting to minimise the mean squared error over a training set. PSO does not require gradient information to function correctly, thus making it a candidate for numerous problems where the gradient is either unavailable or too expensive to calculate.

The first supervised application on neural network training was done by Eberhart and Kenedy [44, 93] by applying the basic PSO to the training of FFNNs. Many others followed with studies that showed the success of PSO on supervised NN training. This includes Mendes *et al.*, who worked on the evaluation of the performance of different neighbourhood topologies on the training of FFNNs [115], and Salerno who used the basic PSO to train recurrent neural networks [139]. The ability of LBEST and GBEST PSO to train FFNNs was evaluated by Hirata *et al.* [73] and Gudise and Venayagamoorthy [71]. Another study on the training of NNs was done by Ismail and Engelbrecht [81] and Van den Bergh and Engelbrecht [158] using product units.

Unsupervised neural network training has not enjoyed as much attention as supervised training. Xiao *et al.* used GBEST PSO to evolve weights for a self-organising map [163]. PSO algorithms have also been used to co-evolve neural networks to approximate evaluation functions of game tree nodes by Messerschmidt and Engelbrecht [116], Franken [63] and Papacostantis *et al.* [128].

Only in recent years has PSO been used in financial applications, with significant success reported. Work has been to apply PSO to trading the stock market [125, 126, 127, 151], portfolio optimisation [27, 56, 86, 150] and credit scoring [66].

4.4 Co-evolution

This section provides a short background study on co-evolution. An introduction to the paradigm is given, highlighting the differences between competitive and cooperative co-evolution. Concepts such as fitness evaluation, fitness sampling and the hall of fame are described. The section ends with a summary of different applications in different fields, including financial applications.

4.4.1 Introduction

Co-evolution is the change in the genetic composition of two or more interdependent species, in response to genetic composition change in one species [38]. It is a mutual evolutionary influence, where each of the species involved exerts selective pressure on each other, allowing the species to evolve and gradually adapt in turn. Co-evolution can be seen as an iterative process, where the involved species participate either in a competitive or cooperative environment, which eventually leads to the gradual improvement of all involved. Therefore, as one specimen becomes superior to another, the second evolves to overcome its inferiority and in turn become superior to the first specimen. The first then repeats the same process, with the process continuing indefinitely. Each specimen in turn offers different challenges, leading to an evolutionary "arms race" [38].

A generic example that depicts the two main different types of co-evolution is given: species A and B in population P_1, together have a competitive advantage of some sort over species C and D in population P_2. Species in population P_2 are forced to adapt in order to ensure their survival by evolving mechanisms to neutralise the competitive advantage of species in population P_1 or even better, to gain an advantage of their own. This is done by species C and D cooperating with each other and sharing knowledge they discover. Once species C and D have successfully done so, species in population P_1 repeat the same process which lead to a tit-for-

tat relationship for an indefinite period, resulting in more adaptable, intelligent and superior species.

The example above primarily demonstrates *competitive co-evolution*, where the fitness of species in population P_1 is an inverted fitness of the competing species in population P_2. A win for the former species ultimately means a failure for the latter. This type of co-evolution is also referred to as *predator-prey co-evolution* and a fine example in biology is described by Holland [77].

Co-evolution can also take place in a cooperative environment [132], referred to as *cooperative co-evolution*, where all species work together in total cohesion. This entails that the species work together as a team and as a single unit within a population. In the example given, an increase in the fitness of specimen A would entail the increase of fitness of specimen B, which forms part of the same population. A win for the former specimen ultimately means a win for the latter. A cooperative environment is also commonly referred to as *symbiosis*. The work in this thesis follows a competitive co-evolutionary approach and thus the following section focuses on this type of co-evolution only.

Co-evolutionary algorithms have two core differences from standard evolutionary algorithms. Evolutionary algorithms operate in a static environment and solutions are usually evaluated against an absolute fitness function. Co-evolutionary algorithms on the other hand operate in a continuously changing environment, locally within each population and globally over other populations. Because of this dynamic environment, absolute fitness functions are difficult to define, but instead fitness is defined relatively, by comparing individual specimens with each other.

4.4.2 Competitive Co-Evolution

Competitive co-evolution [5, 137, 138] takes place in an environment where two or more agents directly compete against each other. It is a process that sees each agent

involved improve iteratively over time in an effort to overcome its competitors. Each new generation sees improved agents with better qualities compared to previous generations: successful qualities get transferred to newer generations and are gradually improved in turn.

It is important to note that with co-evolutionary algorithms, solutions are discovered without any prior knowledge. The only information that is given to the participating agents are the rules of the environment within which they can operate, but no objectives, strategies or general knowledge are provided. This is purely an unsupervised training process, where agents are matched against each other and are then evaluated relative to each other. The discovery of methodologies for machine learning within a competitive environment without the provision of any external knowledge has been an ongoing effort over the past couple of decades [140].

4.4.3 Competitive Fitness

The fitness function used in co-evolutionary algorithms is referred to as *competitive fitness* or *relative fitness*, and is not the same as absolute global fitness, used in standard evolutionary algorithms. No prior knowledge is introduced via a fitness function that could influence the behaviour of involved agents. The only knowledge agents have is the rules of the environment within which they operate. The sole driving force behind the process is the agents of one population performing better than competing agents in other populations. Fitness is therefore purely a relative function between competing agents, expressing the degree of superiority of one agent over another. Therefore, competitive fitness reveals the ability of an agent within a population, and is not relative to a global measurement.

Figure 4.5 depicts ideally how relative fitness may vary between two populations during a co-evolutionary training process, while figure 4.6 depicts the ideal global fitness of two populations. The relative fitness oscillates between two bands, with

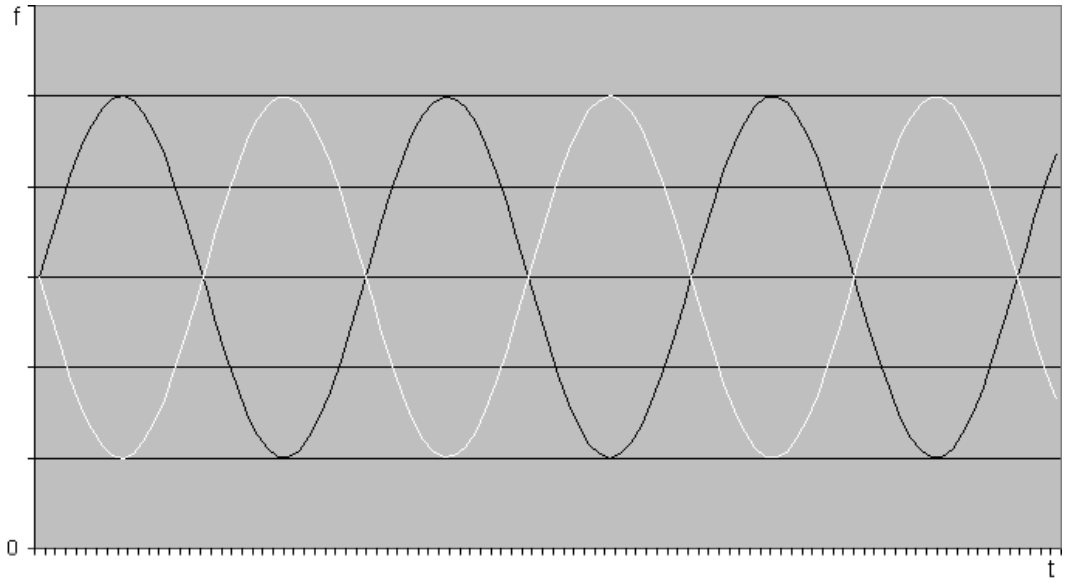


Figure 4.5: Co-evolution relative fitness

the one population overpowering the other in turn over time. In the case where the two populations find themselves at extreme opposite ends, this indicates that the one population is completely overpowered by the other population. The global fitness in figure 4.6 reveals a similar "arms race" pattern, but the difference is that the fitness of each population increases over time. Global fitness reveals how the continuous struggle of each population to overpower its rival population leads to the iterative improvement of each population and the gradual improvement of both over time in an ideal world.

4.4.4 Fitness Evaluation

Assume two populations of solutions P_1 and P_2 co-evolve in a competitive environment. There are three ways in which the fitness of a specific solution $P_1.\vec{x_1}$ could be evaluated relative to population P_2:

- **Simple Fitness** [5, 8, 72]: A sample of individuals is taken from population P_2, and each one of these solutions is evaluated against $P_1.\vec{x_1}$. The fitness

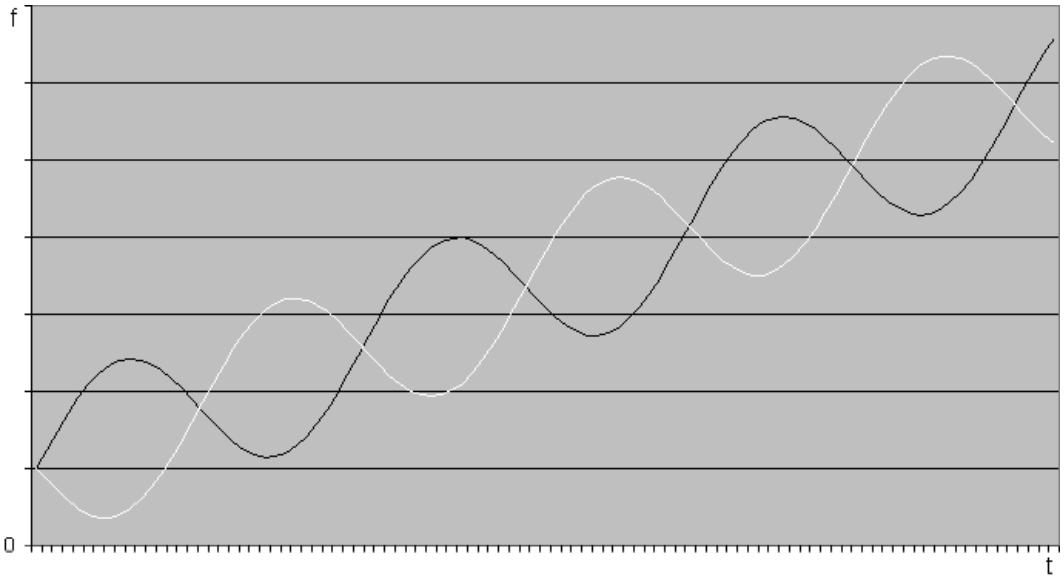


Figure 4.6: Co-evolution global fitness

of the solution $P_1.\overrightarrow{x_1}$ is the number of solutions in the selected sample of P_2 where $P_1.\overrightarrow{x_1}$ was superior.

- **Fitness Sharing** [68]: Fitness sharing is used when it becomes necessary to award solutions that contain unique characteristics. This is mainly done to increase the diversity of solutions in a population so that a larger search space is covered. Fitness sharing can be applied by calculating simple fitness and then dividing this fitness by a value that represents the common characteristics that the solution shares with other solutions within the same population.

- **Competitive Fitness Sharing** [62, 137]: Competitive shared fitness of $P_1.\overrightarrow{x_1}$ is defined as:

$$P_1.\overrightarrow{x_1} = \sum_{i=1}^{P_2.n} \frac{1}{N(P_1, P_2.x_i)} \tag{4.11}$$

where $P_2.n$ is the total number of individuals in P_2 and $N(P_1, P_2.x_i)$ returns the total number of agents in P_1 that defeat $P_2.\overrightarrow{x_i}$. Competitive shared fitness awards agents in P_1 that manage to beat agents in P_2, where few other agents in P_1 managed to do so.

4.4.5 Fitness Sampling

When it comes to selecting the sample against which a solution is to be evaluated, one of the following fitness schemes can be selected [9]:

- **Full competition** [8]: Each solution competes against all other solutions. This scheme is computationally demanding, since every possible pair is evaluated. However, the fact that all solutions are evaluated against each other provides better information regarding the solutions and a more accurate competitive fitness is calculated. This in turn may enhance the overall performance of the algorithm, since there is no possibility of disregarding good solutions.

- **Random sampling**: Random sampling is a scheme that allows each solution to compete against a randomly selected number of solutions. One concern when using random sampling, is that it may exclude favourable solutions in the calculation of the competitive fitness.

- **Bipartite sampling** [72]: With bitrate sampling solutions are divided into two teams, where each team competes against each other. Individuals are tested against one of the teams resulting in less competitions.

- **Tournament sampling** [5]: Tournament selection uses relative fitness measures to select the best opponent individual. Different methods could be used to setup a tournament sampling scheme. One approach would be creating subsets of solutions and finding the best solution for each subset using relative fitness. More subsets are then created using the best solutions and the process is repeated until a final subset of solutions is created which will form the sample solutions.

- **Shared sampling**: With shared sampling the sample solutions are selected as the ones with the maximum competitive fitness.

4.4.6 Hall of Fame

It is important to retain the best solutions from one generation to another, when a high selective pressure is required. With standard evolutionary algorithms, this is achieved via elitism. For co-evolution, Rosin *et al.* [137, 138] introduced the "hall of fame", a mechanism that allows the perseverance of the best solutions throughout evolution. A mechanism such as the hall of fame is necessary in co-evolution, since potentially good solutions may be modified during training. Unlike standard evolutionary algorithms that utilise a global fitness function and can easily retain the best solutions, co-evolution may alter the best solution due to the relative fitness function in use. The solutions in the hall of fame may compete against newly evolved solutions, which may result in the discovery of better solutions.

4.4.7 Applications

Co-evolution has found great applicability in the evolution of strategy-based models for gaming. Applications can be found in a wide range of games, such as tic-tac-toe [5, 6, 63, 116, 128], go [5], checkers [25, 26, 58, 63], backgammon [17, 34, 130, 131, 149], iterated prisoners dilemma [8, 63] and awari [37]. Other areas of application include military purposes [35], classification by using evolving neural networks [72] and controlling agents [98, 117].

More closely related to the topic of this study, a cooperative co-evolution algorithm has been applied to find technical trading rules by evolving genetic programs [14]. Co-evolution is not an extensively applied paradigm in the financial sector, with other financial applications including the simulation of strategic behaviour in markets [133] and co-evolving auction mechanisms [129].

4.5 Conclusion

The model defined in this work, which aims to discover intelligent trading agents, combines three different CI paradigms. These are neural networks, particle swarm optimisation and co-evolution. The paradigms were described in this chapter, highlighting financial applications that are relevant to this study. The FFNN was described, which has been chosen as the architecture used in this thesis. Furthermore, PSO was presented, which will form the unsupervised training technique used to train the neural network agents. Additionally, PSO topologies and parameters were discussed. Finally competitive co-evolution was covered, which is the environment within which agents will compete against each other and progressively improve in the search for the optimal trading agent.

Chapter 5

Security Trading Co-Evolutionary PSO Model

This chapter presents a co-evolutionary particle swarm optimisation (CEPSO) model that is used to discover security trading agents. Section 5.1 describes problems with existing traditional technical market indicator (TMI) rule-based strategies. The section highlights problems with TMI strategies and then defines objectives for a new model to address such problems to improve efficiency. Section 5.2 describes the trade simulation environment within which agent trading strategies are simulated. A description of how trade actions are derived from FFNN output and how capital gains/losses, transaction costs and returns are calculated follows. The model is listed in section 5.3, including an overview of each step. Section 5.4 covers a fundamental part of the CEPSO model, defining the competitive fitness function that is used in the co-evolutionary environment. Finally, a detailed description of the CEPSO model concludes the chapter in section 5.5.

5.1 Traditional Methods and Problems

Conventional TMI rule-based models require the careful selection of indicators and the use of predefined rules that produce sound trade actions [13, 31]. Some examples of such TMIs were presented in chapter 3. Such rule-based models are strictly defined and are very difficult to fine-tune for individual stocks or different stock markets. With just a few parameters to define each TMI, indicators leave much to be desired. Because of the rigidity of such rules, TMIs are commonly used with default parameters and in isolation from other indicators.

The model to be introduced in this thesis aims to discover trading strategies that can offer advantages over conventional TMI rule-based strategies. The model should allow the introduction of an arbitrary number of TMIs, which the model then makes use of selectively. TMIs that are favourable and contribute positively to the quality of discovered solutions should be weighted based on their contribution. No expert trading knowledge should be required for training or to define trading rules. The model should have the ability to search for strong solutions and discover complex trading strategies for securities. Each strategy returned must derive high net profit and low risk trading actions. The model should have the ability to detect trend reversal patterns based on historical price data applied to the TMIs. Finding such patterns in historical data will allow the return of trading strategies that could help in the timing of trend reversals of securities on price data not used for training.

5.2 Trade Simulation Environment

Before describing the CEPSO model, it is necessary to define a trade simulation environment within which strategies can be simulated and evaluated. This section describes the components of such a simulation environment. Deriving trade actions, calculating capital gains/losses, calculating transaction costs and calculating return

on investment are covered in detail, enabling a trading strategy to be evaluated using historical trade data.

5.2.1 Deriving Trade Actions

Given an arbitrary number of TMIs, it is important to describe the manner in which trade actions are derived. A standard three layer FFNN is used for this purpose. The sigmoid activation function is used for the hidden and output layer artificial neurons (AN). The number of inputs used is dependent on the number of time series that are produced by the selected TMIs that are considered, which is explained in more detail in chapter 6.

The output layer consists of a single AN, which will be treated as a trend reversal confidence value in the interval $(0, 1)$. The aim of the trend reversal confidence is to identify switches from up trends to down trends and vice versa, how trend switching is identified is explained in this section. A trend reversal confidence time series, referred to as σ, is produced by the FFNN by providing the values of the time series at each time step and captures the reversal confidence value. Trade actions consist of the actions in the set $\{BUY, SELL, CUT\}$ and are derived from σ:

- if $(\sigma(t) \leq \theta)$ then BUY
- if $(\sigma(t) \geq 1 - \theta)$ then $SELL$
- if $(\sigma(t) > 0.3)$ and $(\sigma(t) < 0.7)$ then CUT
- else no trade action is returned

where $0 < \theta < 0.3$ represents a threshold value of the sensitivity in triggering BUY and $SELL$ actions. The value of θ determines the risk factor that a trading strategy is willing to take on. Small values of θ will result in less riskier trades taking place, while a large θ will return more trades of higher risk. This study has taken the approach

of selecting a small θ. A BUY action entails buying the underlying security, while a $SELL$ action entails short selling the security. A CUT action signals getting out of a position, if one is held. A CUT action means selling the bought stock or buying back the stock that was sold short. An investable amount is defined to determine the amount that is bought or short sold. The investable amount is the total monetary amount available for the trading strategy to invest, which is discussed in more detail in section 5.2.2.

Figure 5.1 depicts in detail how trade signals are derived from σ. The figure illustrates the output of a FFNN, applied over a period in time. The value of $\sigma(t)$ oscillates between 0 and 1, indicating the confidence in the trend reversal of the underlying security. Low $\sigma(t)$ values close to 0 indicates high confidence that a trend reversal from a down-trend to an up-trend is likely. The security in this case is considered to be over-sold and a trend reversal, leading to a price increase, is expected. A high $\sigma(t)$ value close to 1 indicates a high confidence in the trend reversal from an up-trend to a down-trend. In other words, the security is considered

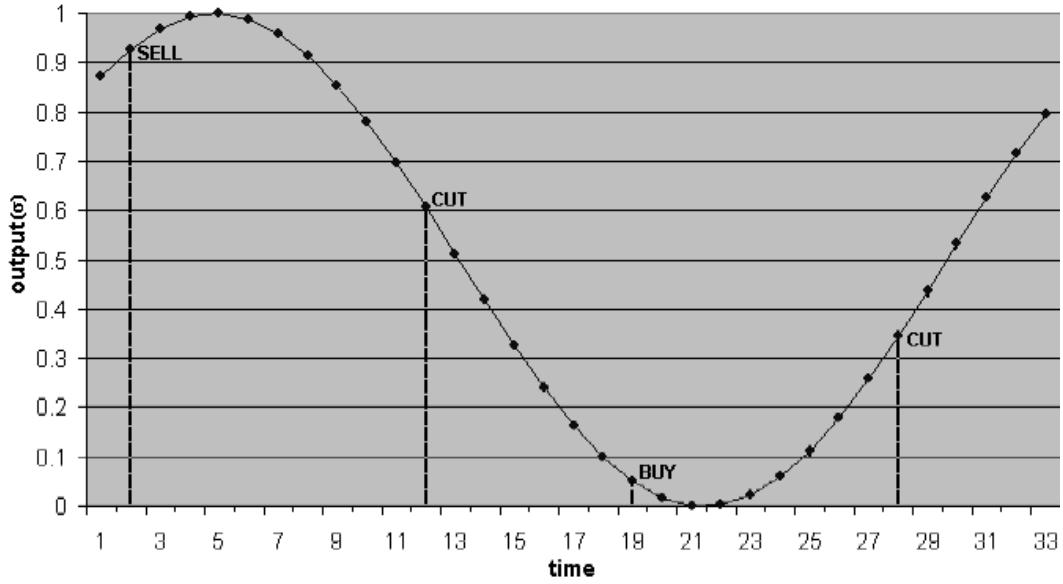


Figure 5.1: Trend reversal confidence example

to be over-bought and a drop in price is expected to take place. The actual trade actions are derived in conjunction with a threshold value θ, which in the case of this example is set to 0.1. The value of θ is a user- defined parameter that determines the trade-triggering sensitivity. For $(\sigma(t) > 0.3)$ and $(\sigma(t) < 0.7)$ there is no confidence in a reversal, indicating uncertainty about the direction of the price in the analysed security.

At time interval 2, $\sigma(t)$ penetrates the $1 - \theta$ level, resulting in a $SELL$ action for the underlying security. The reasoning behind the derivation of a $SELL$ action is that there is a high confidence of a trend reversal from an up-trend to a down-trend for the security. Since there is a high probability in a fall in price, the security is sold short in an effort to take advantage of the possible price decrease. At time interval 19, $\sigma(t)$ penetrates the θ level, causing a BUY action for the underlying security. The action is derived because the trend reversal confidence from a down-trend to an up-trend is very high. The security is bought in this case in an effort to benefit from the possible price rise. A CUT signal is returned in the case where $\sigma(t)$ is between the levels 0.3 and 0.7. Around this mid-level there is much uncertainty with regards to the trend reversal and the trading agent will avoid making any price speculations. In the example presented by figure 5.1, CUT signals are returned at periods 12 and 28.

5.2.2 Calculating Capital Gains and Losses

An investable amount, used either to buy or short sell stocks, is defined. The investable amount is the total monetary amount available for the trading strategy to invest in, for each BUY or $SELL$ action derived. The investable amount can be seen as the investment capital available to the agent. When the FFNN derives a BUY action, the underlying stock is bought to the value of the investable amount. Alternatively when the FFNN derives a $SELL$ action, a short sell of the underlying

stock will take place to the value of the investable amount.

Deriving the trade actions for each time step results in the buying, selling short and trade cutting of the stock at various time points. The number of bought or short sold stocks per trade is calculated, based on the value of the investable amount. Depending on how the stock price fluctuates, capital gains and capital losses are calculated when the trade position is closed. A simple example of such a calculation is given in table 5.1 as a demonstration, using an investable amount of $1,000,000. The agent in the example enters a trade in a specific security, for the first time,

Table 5.1: Capital gains and losses calculation example.

Time	Action	Price	Shares	Capital Gains	Capital Losses
3	*BUY*	$400	2500	-	-
7	*CUT*	$500	2500	$250,000	-
14	*SELL*	$500	2000	-	-
22	*CUT*	$200	2000	$600,000	-
23	*SELL*	$200	5000	-	-
29	*CUT*	$500	5000	-	$1,500,000
35	*BUY*	$500	2500	-	-
40	*CUT*	$400	2500	-	$200,000
Total				$850,000	$1,700,000

at $t = 3$. No prior trading was done, with no capital gains or capital losses values recorded. The agent buys the stock at a price of $\$400$, investing an amount of $\$1,000,000$. A total of $(\$1,000,000/\$400) = 2500$ shares are bought, which are then sold at $t = 7$. Given the increase in the stock price by $\$100$, the agent realises a capital gain of $\$250,000$. A short sell action follows at $t = 14$, at a price of $\$500$ where 2000 shares are sold short. The price drops by $\$300$ at $t = 22$, resulting in a further realisation of $\$600,000$ as capital gain. A capital loss is incurred at $t = 29$, when the price of 5000 short sold shares increases by $\$300$, contributing to a $\$1,500,000$ loss. A further price drop of $\$100$ from $t = 35$ to $t = 40$ results in a capital loss worth $\$200,000$, because a total of 2000 shares were held. Given the

sequence and timing of the agents' trade actions in this example, capital gains worth $\$850,000$ were accumulated and a capital loss of $\$1,700,000$ was suffered. Overall, a loss worth of $\$850,000$ was incurred.

5.2.3 Calculating Transaction Costs

Buying and short selling of stocks come with a transaction cost, payable to the executing broker. It is necessary for such costs to be considered, since costs can be a determining factor in the profitability of the discovered strategies. Transaction costs vary from one broker to another and between different stock markets. For the purposes of this thesis, a transaction cost of 5 basis points (BPS) on the invested amount will be used for each trade entry and each trade exit. Additionally, 36.5 BPS per annum on the invested amount will be used as a script lending fee. Based on an investable amount of $1,000,000, this results in transaction costs of $500 per trade entry, $500 per trade exit and $3650 per annum for script lending (or $10 per day). Table 5.2 portrays an example of transaction costs, based on a simplistic scenario. At $t = 22$ a script lending fee of $\$80$ is payable for the eight days the stock was borrowed, while an additional fee is payable at $t = 29$ for a further six days. In total, transaction costs worth $\$4160$ were payable to the executing broker for this example.

Table 5.2: Transaction costs calculation example.

Time	Action	Transaction Costs
3	*BUY*	$500
7	*CUT*	$500
14	*SELL*	$500
22	*CUT*	$500 + (8*$10) = $580
23	*SELL*	$500
29	*CUT*	$500 + (6*$10) = $560
35	*BUY*	$500
40	*CUT*	$500
Total		$4160

5.2.4 Calculating Return on Investment

The *return on investment*, otherwise referred to as *returns*, is a ratio of the profits or losses on an investment over the total capital invested. Returns are calculated for a specific period of time, using the following equation:

$$returns = \frac{EMV - BMV}{BMV} \tag{5.1}$$

where EMV is the value of the investment at the end of the period and BMV is the value of the investment at the beginning of the period. It is common practice to annualise the returns, in order to make returns from different period lengths comparable.

In the context of the trade simulation environment presented in this section, the returns are calculated as the capital gains/losses over the investable amount:

$$returns = \frac{CG - CL}{IA} \tag{5.2}$$

where CG are the capital gains, CL are the capital losses and IA is the investable amount. For the example presented in table 5.1, the returns are -$\$850,000/\$1,000,000 = -0.85$ or -85% for the 40 days the strategy traded.

5.3 The CEPSO Model Step-by-Step

This section lists the steps of the CEPSO model, providing an introductory overview. More details on the model is provided in section 5.5.

1. Calculate the TMI time series data, based on the security price data as described in chapter 3. Divide the TMI time series data into two sets, namely an in-sample and out-sample TMI time series data set. If the TMI time series consists of n data points, the in-sample data set would consist of all sequential data points from the beginning of the time series to m, and the out-sample data set all sequential data points from m to n, where $n > m$.

2. Create a single swarm of particles and randomly initialise the position of each particle within the range $[-r, r]$.

3. Set the velocity of each particle within the swarm to zero.

4. Initialise each particle's personal best to its current position.

5. Repeat the following steps for a total of n epochs:

   A. Use the current position vector of each particle within the swarm and create a population of feed forward neural networks by assigning the particle position vectors as FFNN weight vectors.

   B. Using the in-sample TMI data set to derive the FFNN trend reversal confidence time series.

   C. Using the in-sample trend reversal confidence time series, calculate the performance metrics for each solution within the population, by simulating the derived BUY, $SELL$ and CUT signals.

   D. Calculate the competitive fitness for each solution using the in-sample data. Each solutions' performance metrics are considered in the calculation, which is derived from the in-sample data. More detail on how the competitive fitness is calculated is given in section 5.4.

   E. Add the best solution from the population to the hall of fame.

   F. Update each particle's fitness to the calculated competitive fitness of the agent.

   G. Update each particle's personal best position.

   H. Update the neighbourhood best position for each particle.

   I. Update the velocity for each particle.

   J. Update the position of each particle in the swarm.

6. Using the out-sample TMI data set, derive the FFNN trend reversal confidence time series for each solution in the hall of fame.

7. Using the out-sample TMI confidence time series, calculate the performance metrics for each solution in the hall of frame, by simulating the derived BUY, $SELL$ and CUT signals.

8. The best solution within the hall of fame needs to be determined based on the out-sample data. Calculate the competitive fitness for each solution in the hall of fame using the out-sample data. Return the solution with the highest competitive fitness for out-sample data as the best solution the model has produced.

5.4 Competitive Fitness Function

Given a set of trade agents, a fitness value is assigned to each agent indicating its relative strength or weakness with respect to other agents in the same set. The competitive fitness introduced in this section is defined based upon two trade performance metrics that are calculated for each agent, which includes a net profit and the Sharpe ratio. It is important to note that these performance metrics can be calculated individually for each agent in complete isolation from other trade agents. The performance metrics themselves are not the relative measures but merely represent straightforward metrics of the performance of the agent.

The net profit of a trade agent is calculated by taking the capital gains of the strategy and subtracting the capital losses and transaction costs. This *profit and loss* (P&L) measure is defined as:

$$P\&L = CG - CL - TC \tag{5.3}$$

where CG represents the capital gains, CL the capital losses and TC the transaction costs of the strategy.

The *Sharpe ratio* (SR) was developed by William F. Sharpe to measure risk-adjusted performance [11]. The ratio is calculated by subtracting a risk-free rate from the rate of return of an asset or trading strategy. The result is then divided by the standard deviation of the returns. The Sharpe ratio is defined as:

$$SR = \frac{r_S - r_F}{\sigma_S} \tag{5.4}$$

where r_S is the annualised return of the security, r_F is an annualised benchmark risk free rate, and σ_S the annualised standard deviation on the returns of the security. For the calculation of the standard deviation of the returns, the daily returns are commonly considered. The Sharpe ratio highlights if returns are due to smart investment decisions or as a result of excess risk-taking. This measure is very useful, because although one strategy may return higher returns than another, a strategy is only a good investment if those higher returns do not come with too much additional risk. The greater the Sharpe ratio, the less risky the trading strategy is considered to be. Sharpe is the most common risk metric used in the financial sector and works very well when trading risk needs to be assessed.

For each trade agent in a given set of agents, the normalised weighted summation of the agents' P&L and SR is taken. The performance metrics are normalised to the minimum and maximum performance metric out of all the agents within the set. The following equation defines the competitive fitness function for a specific agent:

$$F = \left[\frac{P\&L - min_{P\&L}}{max_{P\&L} - min_{P\&L}}\right] + \left[\frac{SR - min_{SR}}{max_{SR} - min_{SR}}\right] \tag{5.5}$$

where $max_{P\&L}$ and $min_{P\&L}$ represents the maximum and minimum trade agent P&L in the set of agents, while max_{SR} and min_{SR} represent the maximum and minimum agent SR in the set of agents.

The competitive fitness function attempts to evaluate the relative performance of each solution within a set of solutions, by considering a weighted balance between net profit and risk. The fitness function directs trading agents in making the highest net profit at the lowest risk possible. By considering equation (5.3), the agent in fact attempts to maximise capital gains and minimise capital losses together with transaction costs. The consideration of equation (5.4) allows low risk solutions to be returned by maximising strategy returns and minimising the standard deviation of the returns. considering equation (5.5) closely, it can be deduced that a relative fitness value of 2 represents a solution that is superior in P&L and SR in the set of solutions, while a value of 0 represents the most inferior solution in the set. Note that the competitive fitness value can not be used to compare solutions that were derived from within different sets of solutions, since different maximum and minimum performance metrics may exist in each separate set.

5.5 CEPSO Model Described

This section describes the CEPSO model in more detail. The first step of the CEPSO model is data preparation. Price data is separated into two sets, an in-sample and out-sample set. The former set is prepared to be used for training purposes, while the latter is used to evaluate the generalisation ability of discovered strategies. Each set is applied to the TMIs used in the model, deriving in-sample and out-sample TMI time series data. If the TMI time series consists of n data points, the in-sample data set would consist of all sequential data points from the beginning of the time series to m and the out-sample data set all sequential data points from m to n, where $n > m$.

PSO has been proven to be very effective as an unsupervised NN training algorithm, as described in chapter 4, section 4.3.4. The CEPSO makes use of unsupervised learning through competitive co-evolution to allow NN training. A single swarm

of particles is created, each particle representing a security trade agent. For each particle in the swarm, the position is randomly initialised uniformly over the entire search space. This will enable the algorithm to better converge to a strong solution. A range from which random weight values can be selected was defined by Wessels and Barnard [161] for this purpose. The ranges was defined as $[\frac{-1}{\sqrt{fanin}}, \frac{1}{\sqrt{fanin}}]$, where $fanin$ is the number of connections leading to an AN. This initialisation of weights close to zero has shown to be very efficient, facilitating convergence to optimal points within the search space. The personal best position of each particle is set to the particle's initial position. A population of FFNNs is created by using the particle position vectors as weight vectors. The trend reversal confidence signal for each neural network is then computed for the in-sample TMI data during training, considering a historic time window of size t. Trading actions that define BUY, $SELL$ and CUT actions are derived, as described in section 5.2.1. The trading actions are executed for each time step, with capital gains, capital losses and transaction costs calculated, as explained in section 5.2.

The performance of each particle (representing a FFNN) is measured using the relative fitness function defined in equation (5.5). Based on the calculated performance metrics, the competitive fitness for each FFNN strategy is computed using full competition sampling, described in more detail in section 6.2.2. The fittest FFNN is added to a hall of fame, allowing the perseverance of strong strategies throughout the training process. A PSO algorithm is then executed to update each particle's best position. It is important to note that, since a competitive fitness is used to evaluate the solutions within the swarm for each generation, the competitive fitness cannot be used to compare solutions between different generations. The personal best position of the particle is updated with the position with the highest competitive fitness, comparing the current and existing personal best positions. The neighbourhood best position for each solutions is then updated, together with the velocity and particle

position.

The training process takes place for a predefined total of n epochs, with each epoch contributing the best in-sample strategy of the population to the hall of fame. After the n epochs are executed, all the strategies in the hall of fame are evaluated against each other, by using the competitive fitness function on all solutions within the hall of fame. Previously the solutions were evaluated based on their out-sample data, the objective with re-evaluating the hall of fame is to do so based on out-sample data. The out-sample data is used in this case, with the highest fitness solution returned as the best strategy.

5.6 Conclusion

This chapter presented the CEPSO model that forms the FFNN unsupervised trainer. The chapter explained the reasoning behind the selection of the model and the benefits over conventional TMI rule-based strategies. A trade simulation environment was described that allows the simulation of trading strategies. The manner in which trading actions are derived, the calculation of capital gains/losses, transaction costs and returns are explained in detail with accompanying examples. A step-by-step listing of the model then followed. The competitive fitness function was presented, used in the competitive co-evolutionary environment to evaluate strategies against each other. A detailed CEPSO model description then ended the section.

Chapter 6

Empirical Study

This chapter examines the performance of the co-evolutionary particle swarm optimisation (CEPSO) model. The model is applied to the stock price data of eight different companies, discussed in section 6.1. The section also covers the technical market indicator time series used and how the data is generally prepared for the model. Section 6.2 covers the experimental procedure, defining objectives and introducing the initial CEPSO model set-up. Algorithm parameters and configurations are examined in section 6.3, with the optimum model set-up discovered. The best discovered strategies are compared against two benchmarks in section 6.4, highlighting the effectiveness of the model.

6.1 Data Preparation

This section describes the data preparation for the empirical study, which includes the stock data selection and the technical market indicators to which data is applied to.

6.1.1 Stock Data

The top four US and UK companies by market capitalisation were selected, as defined by the *FT Global 500* [154]. The FT Global 500 is an annual snapshot of the largest 500 companies worldwide, ranked by market capitalisation. Its purpose is to highlight how corporate fortunes change over time in different countries and industries. The selection of the stocks was made based on the list published on the 31st March 2008. Refer to appendix C, table C.1 for a layout of the stocks used in this chapter, together with their corresponding worldwide rank, country of origin, currency, industry and market capitalisation. The daily price graphs for all eight companies are also illustrated in appendix C, in the domicile currency of each company. The data for a period of eight and a half years was used, which included data for the dates 1st January 2000 to 30th June 2008. The in-sample data was selected as 75% of the data, which consisted of the dates 1st January 2000 to 31st March 2006. The remaining data was used as the out-sample data set, between the dates 1st April 2006 to 30th June 2008.

The period 1st January 2000 to 30th June 2008 consists of a variety of stock market crisis events, making it ideal for training purposes. It is ideal because during these market events price movements were irrational and volatile, allowing the discovery of agents that can deal with such extreme events. The date period that has been selected includes the following market events:

- **Dot-com bubble**: The dot-com bubble roughly covered the period 1995-2001, which saw a rapid increase of companies in the internet sector and other related fields. It reached a climax on 10 March 2000, when the bubble "burst," causing dramatic falls in share prices in many involved companies, resulting in many of the companies going bust.

- **9/11**: The attacks on the World Trade Centre on 11 September 2001 had

Table 6.1: TMI time series for empirical study.

Indicator	Time Series
Aroon	AroonUp
Aroon	AroonDown
Bollinger Bands	%b
RMI	RMI
MACD	PriceMomentum
MACD	PriceTrigger

major economic effects. An initial shock caused the global stock market to drop sharply, while in the long-term stocks of companies in some sectors were hit particularly hard.

- **Subprime mortgage crisis**: This is an ongoing economic problem, which became noticeable through liquidity issues in the global banking system during the fourth quarter of 2006. A global financial crisis took place through 2007 and 2008, with a number of mortgage lenders declaring bankruptcy in a matter of weeks. The market has been filled with concerns of a major global credit crunch, which have affected all classes of borrowers.

6.1.2 Technical Market Indicator Time Series Data

The in-sample and out-sample stock price data of the selected companies, as described in section 6.1, are applied to the chosen technical market indicators covered in chapter 3. The time series of the technical market indicators (TMI) used in this empirical study are listed in table 6.1. The application of the TMI to the price data results in the creation of in-sample and out-sample TMI data sets. The first set is used for training, while the second set is used for evaluation. The TMI time series values are normalised in the range [-1,1], to make their range consistent with each other.

The specific indicators were selected because of their popularity and the fact that

the time series they produce oscillate in a fixed range [31]. The oscillation in a fixed range makes them practical in the context of neural networks, since they can easily be normalised for use as neuron inputs. Furthermore, they expose a variety of price properties throughout time, including supply, demand, momentum, volatility, trend, sentiment and retracement.

6.2 Experimental Procedure

The empirical objectives that will be studied and analysed in this thesis are outlined in section 6.2.1. The initial set-up of the CEPSO model is described in section 6.2.2. The default values used for financial parameters are initially described. The section then describes neural network, PSO and co-evolution configurations used in the empirical study.

6.2.1 Objectives

The following empirical objectives will be studied and analysed, with the in-sample and out-sample performance considered:

- An analysis of different particle swarm optimisation (PSO) topologies and how they affect the quality of discovered strategies.

- An investigation of swarm population size combinations with feed forward neural network (FFNN) hidden layer size. A study of how an increase in size of swarm population size and hidden layer size affects the model, keeping in mind issues of overfitting and computational complexity. These parameter combinations are additionally investigated against different PSO topologies.

- An examination of the change in performance for different trading rule sensitivity thresholds (θ).

- A study of whether the given model is successful in discovering optimal trading agents, by comparing its performance against two benchmark strategies.

6.2.2 CEPSO Model Initial Set-up

Financial Parameter Configuration

An investable amount of 1,000,000 currency units is utilised in the trade simulation environment, as described in chapter 5, section 5.2. This is the total capital available for agents to buy or short sell stocks, on a trade-by-trade basis. The currency unit is determined by the domicile currency of the stock. For US companies the US Dollar (USD) is used, while the Pound Sterling (GBP) is used for UK companies.

For the Sharpe ratio calculations, an annual risk-free rate of 3% was used for the US companies and 6% for the UK companies. The risk-free rates were chosen based on the applicable interest rates for the US and UK at the time this empirical study was conducted.

Neural Network Configuration

A standard three layer FFNN is used to produce the trend reversal confidence, from which trading actions are derived. The sigmoid activation function are used for hidden and output neurons.

The size of the FFNN input layer is six, which is the total number of TMI time series as defined in table 6.1. The size of the FFNN hidden layer is investigated with values of 2, 4, 6, 8 and 10 in section 6.3.1. Based on the results of the empirical study, an investigation of more than 10 hidden units was not necessary. This is due to the increased computational intensity that is introduced with no significant improvement visible.

A single neuron forms the output layer of the neural network, which returns a value in the range $(0, 1)$, indicating a trend reversal confidence, as described in

section 5.2.1. The threshold, θ, used to derive trade actions from the FFNN output is initially set to 0.05, but values of 0.1, 0.2 and 0.3 are examined in section 6.3.2. Larger values are not considered, since 0.3 is the level at which CUT signals are returned, as described in section 5.2.1.

PSO Configuration

The PSO algorithm is executed for a total of 350 epochs for each simulation. The value ϕ for the inertia weight is set to 0.729844 and the acceleration constants c_1 and c_2 are set to 1.496180. These three parameters satisfy the relation defined by van den Bergh [157], ensuring convergent behaviour. The swarm size is investigated in this empirical study, with values 10, 25, 50, 100, 150 and 200 in section 6.3.1. Different PSO topologies, such as GBEST, LBEST and Von Neumann, are also studied in section 6.3.1. A standard PSO algorithm is used, as introduced by Kennedy and Eberhart [91, 92].

Co-evolutionary Configuration

A full competition fitness sampling is used, with other fitness sampling schemes not considered. Full competition fitness sampling is used because it results in a better estimation of relative fitness compared to schemes where only a sub-sample of competing solutions is considered. The competitive fitness function defined in equation (5.5) in section 5.4 normalises the performance metrics for all available trading agents in each iteration, resulting in the most accurate estimation of relative fitness.

6.3 Experimental Analysis

Appendix D depicts all the experimental result tables that this section refers to. An overview of the experimental results is given below.

Tables D.1, D.2 and D.3 lists the average and standard deviation of the annualised returns for the GBEST, LBEST and Von Neumann PSO topologies, together with the combination for different particle swarm sizes and hidden neurons. The profit and loss (P&L) and Sharpe ratio is tabled in the same fashion in tables D.4, D.5, D.6, D.7, D.8 and D.9. A total of 30 simulations were executed for each permutation of the three parameters (swarm size, hidden layer size and topology) for each company. Performance associated to the increase of hidden layer neurons is depicted from left to right, while the performance associated from top to bottom is relevant to the increase of the PSO particle swarm size. The results for all eight company stocks are combined in these tables, giving an overall view of returns, P&L and Sharpe ratios regardless of the stock. By combining the companies together in these tables, 180 simulations result for each table entry. The reason why all eight companies are combined together is to keep the number of tables to a manageable number, with nine tables to compare instead of seventy two. The company-by-company results are listed in tables D.10, D.11 and D.12 for the best swarm size and hidden layer set-up of the Von Neumann and LBEST topologies. Table D.13 depicts the annualised returns for different trend reversal confidence parameters on a company-by-company basis.

All tables clearly indicate the different parameter combinations used to produce the results, on the top left column of each table. The top half of each table lists the averages for the simulations, while the bottom half lists the standard deviations. The left half lists the in-sample results, while the right half lists the out-sample results. The averages of the average and standard deviation results are indicated in the last column and last row of each table.

Solutions with combinations for the three parameters swarm size, hidden neuron size and topology will be referred to using the following notation (swarm size, hidden neuron size, topology). As an example, the solution (100, 6, Von Neumman) will refer to a solution with a swarm size of 100, 6 neurons in the hidden layer using a

Von Neumann topology.

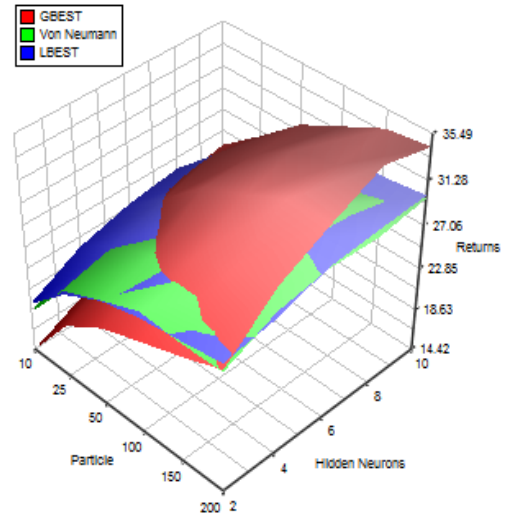
6.3.1 Topology vs. Swarm Size vs. Hidden Layer Size

Figure 6.1(b) illustrates together with the out-sample returns in tables D.1, D.2 and D.3, that the returns of GBEST are considerably lower compared to Von Neumann and LBEST. This can be explained by the fact that GBEST explores less compared to the other topologies. Graph 6.1(a) indicates that GBEST has high in-sample returns for large swarm size and hidden layer size combinations, which is due to the overfitting of trained data.

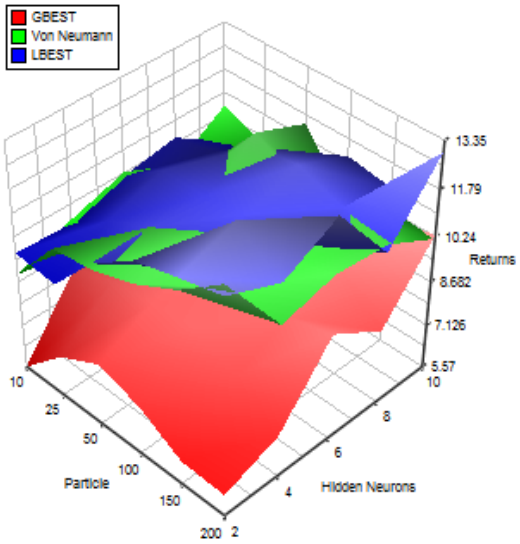
The highest GBEST solution for out-sample data has a return of 10.34%, occurring at (50, 10, GBEST). The Von Neumann and LBEST topologies both have their highest return solutions over 13.0%. A solution with a return of over 13.0% occurs once for the Von Neumann topology, at (200, 2, Von Neumann) with a return of 13.35%. The LBEST out-sample returns in table D.3 contains solutions with similar quality at (150, 4, LBEST) and (200, 6, LBEST) with returns of 13.21% and 13.14% respectively.

A 95% confidence interval using a two sample t-test is utilised for the following comparison, based on 180 observations for each sample. The two sample t-test is compared against a critical value of 1.97; t-test values larger than the critical value are considered significantly different. The top Von Neumann solution based on out-sample returns is significantly different to the GBEST solution, the t-test value considering the two samples (50, 10, GBEST) and (200, 2, Von Neumann) is 1.99. The top LBEST solution (150, 4, LBEST) falls short on the t-test at 1.95 against GBEST and is therefore not significantly different when considering the out-sample returns at a 95% confidence.

Examining tables D.4, D.5, D.6, D.7, D.8 and D.9 in conjunction with the figures in 6.2, the following is observed:



(a) Returns in-sample



(b) Returns out-sample

Figure 6.1: Annualised returns (%) for each topology

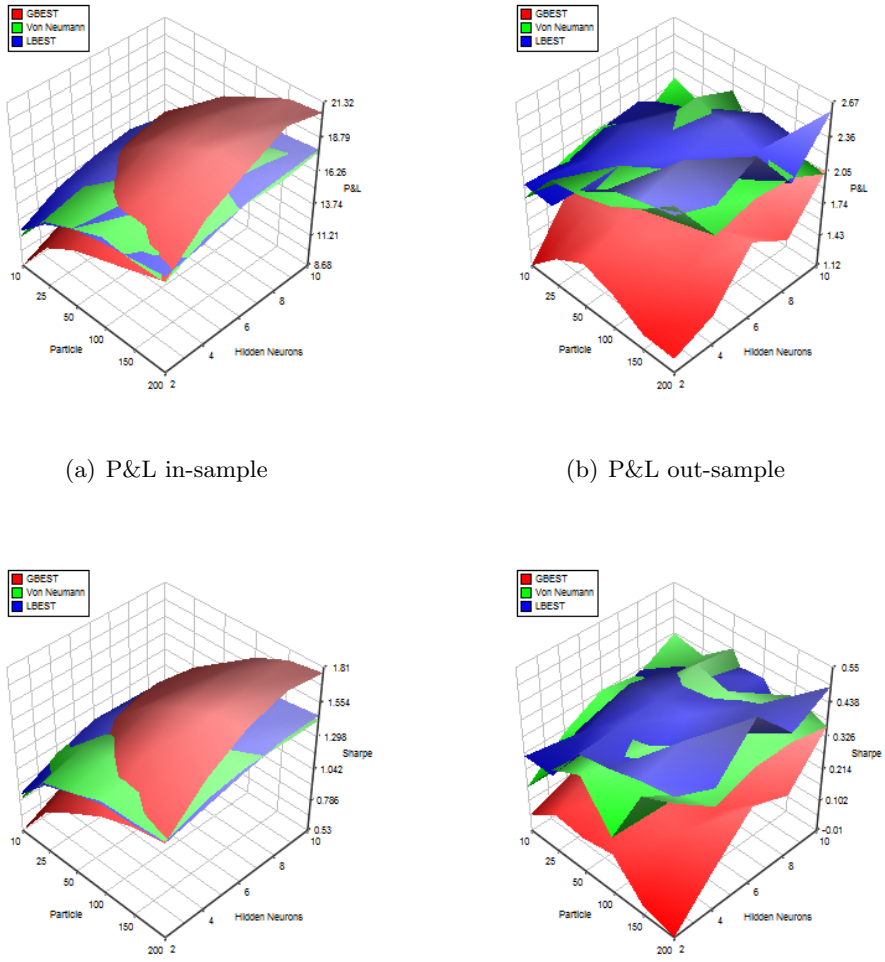
- **Von Neumann**: The two highest out-sample P&L solutions consists of values of 2,670,000 at (200, 2, Von Neumann) and 2,450,000 at (150, 2, Von Neumann). The top two Sharpe solutions consist of 0.46 at (50, 8, Von Neumann) and 0.45 at (200, 2, Von Neumann). Considering that (200, 2, Von Neumann) has the highest returns, highest P&L and a high Sharpe ratio, it is chosen as the favourite Von Neumann solution.

- **LBEST**: The top two P&L solutions, consists of 2,640,000 at (150, 4, LBEST) and 2,630,000 at (200, 6, LBEST). The top three Sharpe solutions consist of 0.55 at (200, 6, LBEST) and 0.49 at both (150, 4, LBEST) and (200, 10, LBEST). All three solutions have noteworthy performance features, but it is solution (150, 4, LBEST) that stands out. The reason is because its P&L and Sharpe performance is high using the smallest PSO particle swarm size and the smallest number of hidden neurons out of all three solutions. Solution (150, 4, LBEST) is selected as the favourite LBEST solution, since it is less computationally expensive because of the small swarm and hidden layer size.

- **GBEST**: The top solution based on P&L is 2,070,000 with a Sharpe of 0.37. The best GBEST solution based on all three performance metrics considered is (50, 2, GBEST).

The best solutions for the Von Neumann and LBEST topologies are therefore (200, 2, Von Neumann) and (150, 4, LBEST). Results of these topologies are compared in tables D.10, D.11 and D.12 together with figures 6.3 on a company-by-company basis. These three tables break down the performance for each solution against each individual company for a more detailed comparison. The in-sample vs. out-sample results and averages vs. standard deviation results are portrayed in the same fashion as all previous tables.

The performance breakdown for each individual company shows that the two selected configurations perform very similarly for out-sample and in-sample data, with one topology slightly outperforming the other for some companies and vice versa. Based on table D.10, the LBEST topology can be identified as having slightly higher out-sample average returns for General Electric, AT&T, HSBC and BP. Exxon Mobil, Microsoft, Vodafone and Rio Tinto Group have slightly higher out-sample average returns for the Von Neumann topology. It must be pointed out that there



(a) P&L in-sample

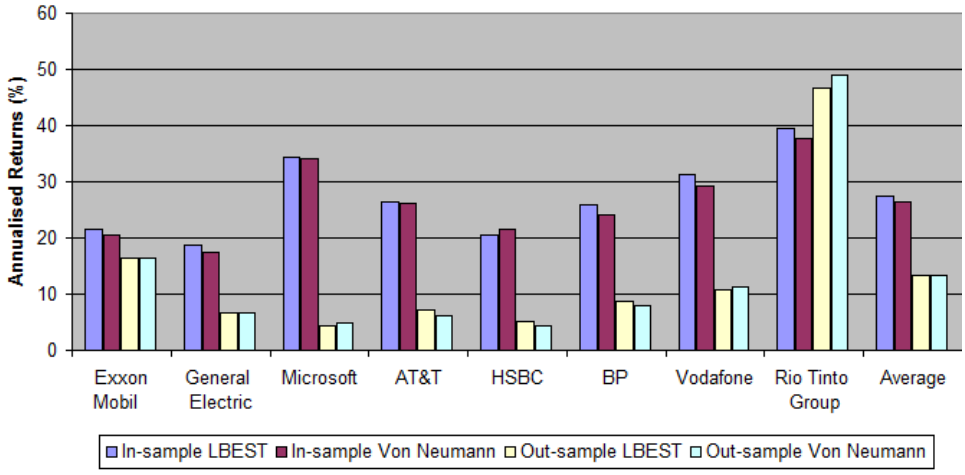
(b) P&L out-sample

(c) Sharpe in-sample

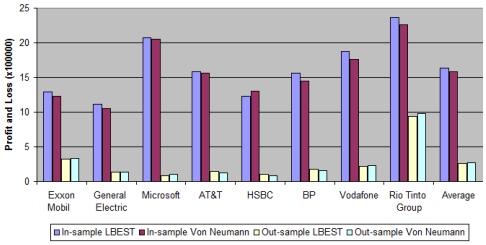
(d) Sharpe out-sample

Figure 6.2: P&L and Sharpe ratio for each topology

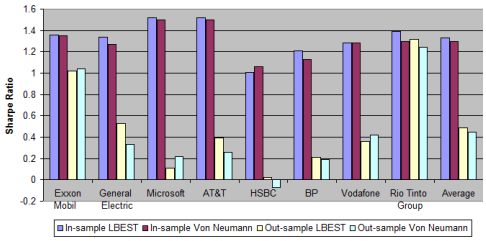
is no significant difference between these two solutions based on average returns for out-sample and in-sample data. LBEST performs an average of 1.0% better than Von Neumann, with all company returns higher for this topology, except for HSBC. Tables D.11 and D.12 confirm that the performance of LBEST and Von Neumann are similar with no significant difference between the two. Given the better performance of LBEST for in-sample data and the fact that it has a smaller swarm size compared to the Von Neumann set-up, (150, 4, LBEST) is selected as the overall favourable



(a) Annualised returns (%)



(b) P&L



(c) Sharpe ratio

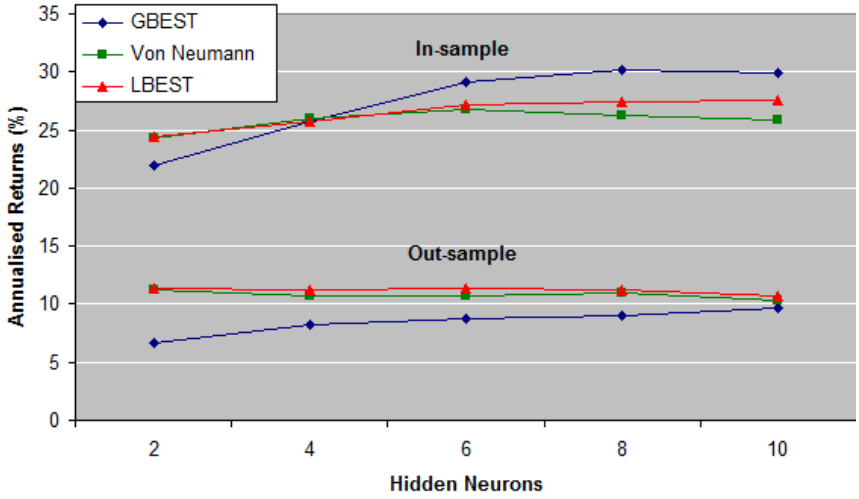
Figure 6.3: Performance metrics for best Von Neumann and LBEST solutions

solution offering optimal results with the least computational complexity.

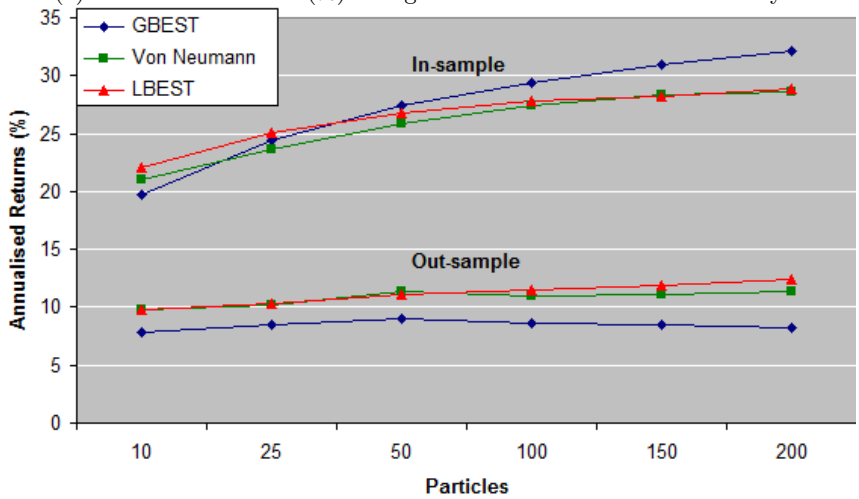
Increasing the Hidden Neurons

Tables D.1, D.2 and D.3 summarises the annual returns for the different topologies together with figure 6.4(a), the following observations can be made by studying the pattern when the number of hidden neurons are increased. By examining the annualised return averages, a definite performance increase can be identified for the in-sample data when neurons are increased. Examining the out-sample data, a different pattern is observed. It seems as if increasing the hidden neurons results in a decrease in performance for the out-sample data. These observations are related to

the overfitting of data during the training process. The introduction of more neurons to the neural network architecture allows more degrees of freedom, resulting in an improvement of the in-sample data. This does not favour out-sample data, since the neural network may be overfitting in-sample data patterns. For the given data, more than six neurons in the hidden layer causes a substantial drop in performance for out-sample data.



(a) Annualised returns (%) change for an increase in the hidden layer



(b) Annualised returns (%) change for an increase in the particle size

Figure 6.4: Performance Topologies

Increasing the Swarm Size

Tables D.1, D.2, D.3 and figure 6.4(b) indicate that there is a direct correlation between swarm size and performance, for in-sample and out-sample data. This is visible by observing the increase in annualised return averages for all three topologies as the swarm size increases. This is attributed to the improved exploration capability of the particle swarm, when more particles are introduced. The more particles, the more information can be derived from the search space and is shared among particles, allowing better solutions to be found. The optimum swarm size is determined by finding a size that offers a good trade-off between high performance and low computational complexity. Based on the investigation conducted in this section, a particle swarm size of 150 was found to be optimum for the LBEST topology.

6.3.2 Trading Sensitivity Threshold

A study is performed on the threshold values used to derive the trading actions from the trend reversal confidence. The value of θ determines the risk factor that a trading strategy is willing to take on. Small values of θ will result in less riskier trades taking place, while a large θ will return more trades of higher risk. This study has taken the approach of selecting a small θ, a value of 0.05 was used thus far. Table D.13 investigates larger threshold values, in an effort to increase annualised returns by producing more trades with smaller confidence values.

The out-sample average annualised returns indicate that larger values contribute to smaller returns. This highlights that lowering the confidence threshold yields smaller returns even though more trading takes place. The corresponding average annualised returns for θ values of 0.05, 0.1, 0.2 and 0.3 are 13.21, 13.09, 12.13 and 10.77. Since no benefits are seen with a change in the threshold, the optimal parameter value remains as $\theta = 0.05$.

6.4 Benchmarks

Each company stock price forms a different problem, so different model configurations are suitable for different companies. The empirical procedure thus far aimed at fine-tuning a general configuration that would be the most suitable for all eight investigated companies. The best configuration for each individual company is not chosen to be compared against the benchmarks, but rather the results derived from the configuration that was optimum overall. The set-up (150, 4, LBEST) with $\theta = 0.05$ is chosen to be compared against the benchmarks.

6.4.1 Rule Based Results

A good combination of two technical market indicators is that of Bollinger Bands and RSI, as suggested by John A. Bollinger [19]. The two indicators complement each other very well and can be used to produce sound trading rules. Table 6.2 depicts the annualised results of using such rules on the eight selected companies. The annualised returns of the trading rules are compared with the returns of the agents discovered via the CEPSO model.

Comparing the strategies, the CEPSO strategies significantly outperform the rule-based model for in-sample data. The returns are considerably higher for all eight companies, which is to be expected since the in-sample data was used for training and the neural network agent has taken full advantage of it. The out-sample results highlight that the CEPSO strategies are superior for all companies, except for General Electric and AT&T. In the case of General Electric, the CEPSO strategy produced smaller annual returns by 3.14%, compared with the rule-based strategy. For AT&T the performance of the benchmark is even larger, 13.02% better than CEPSO. For the remaining six companies the CEPSO agent was superior, indicating that the CEPSO model overall outperforms the Bollinger Bands/RMI strategy. On average the CEPSO agents produces 21.24% more returns for the in-sample data and 9.09%

for the out-sample data. The out-performance for out-sample data is by a factor of 3.2, clearly highlighting its superiority over the benchmark.

6.4.2 Buy-And-Hold Results

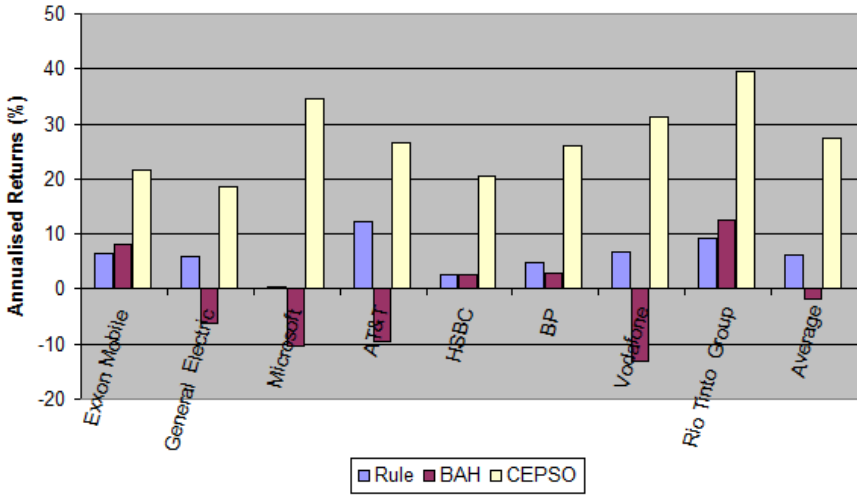
The buy-and-hold (BAH) strategy is more suitable as a long-term investment strategy benchmark, rather than a short-term trading strategy. Nevertheless, it is the most commonly used benchmark for trading applications and is presented in this section.

Buy-and-hold is a passive investment strategy in which an investor buys securities and holds them for a long period, regardless of fluctuations in the market. An investor who employs a buy-and-hold strategy selects favourable securities and invests in them indefinitely. This strategy is not concerned with short-term price movements and technical indicators.

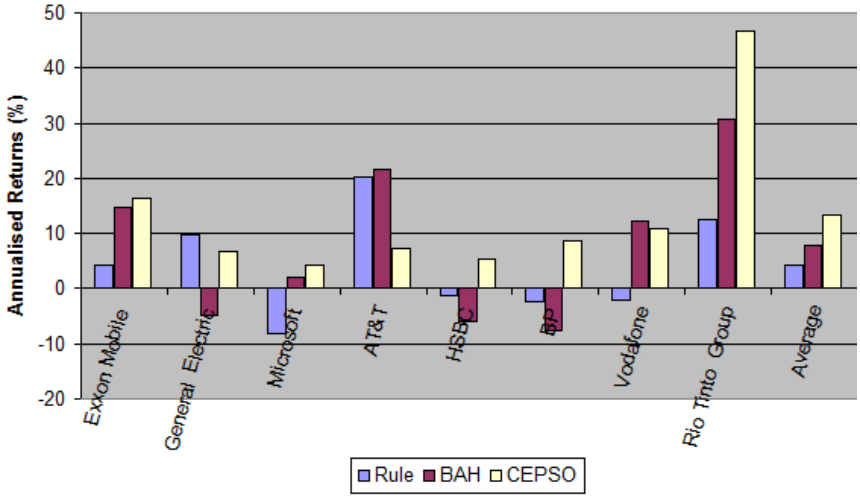
Once again, the CEPSO agent proves to be superior to the benchmark for in-sample data, yielding higher returns. The discovered agents for out-sample data seem to be generally superior, outperforming the buy-and-hold strategy for all companies, except two. The buy-and-hold strategy has higher returns for AT&T and Vodafone only. The CEPSO agent out-performance for in-sample data is by 29.0% and out-sample data by 5.3%, indicating that the discovered agents are indeed superior.

Table 6.2: Benchmarks vs CEPSO model.

	In-Sample			Out-Sample		
Name	Rule	BAH	CEPSO	Rule	BAH	CEPSO
Exxon Mobil	6.47	8.07	21.6	4.33	14.81	16.33
General Electric	5.97	-6.15	18.67	9.77	-4.78	6.63
Microsoft	0.28	-10.48	34.47	-8.09	1.94	4.3
AT&T	12.36	-9.66	26.5	20.25	21.57	7.23
HSBC	2.64	2.54	20.57	-1.39	-5.90	5.23
BP	4.94	2.82	25.97	-2.23	-7.48	8.6
Vodafone	6.74	-13.21	31.23	-2.17	12.28	10.73
Rio Tinto Group	9.16	12.46	39.47	12.50	30.77	46.63
Average	6.07	-1.70	27.31	4.12	7.90	13.21



(a) Strategy Returns In-Sample



(b) Strategy Returns Out-Sample

Figure 6.5: Returns

6.5 Conclusion

This chapter presented an the empirical study of the competitive CEPSO model presented in this thesis. The data preparation for the experiments was described, covering the TMI time series and company price data used. Experimental objectives were stated and the initial model configuration defined. The objectives of the empirical study was to improve the model by discovering a set of optimal parameters and model variations, constituting to improved in-sample and out-sample results. A

model configuration that consisted of a swarm size of 150 particles and a neural network with four hidden neurons, using the LBEST topology with a reversal threshold confidence value of $\theta = 0.05$, performed optimally among the different topologies investigated. The CEPSO strategy results were then compared against a TMI rule-based and buy-and-hold strategy, with the CEPSO strategy proving to be superior to both benchmarks. This shows that the model is in fact successful in discovering high quality trading agents.

Chapter 7

Conclusion

This chapter serves as a conclusion to the thesis. Section 7.1 summarises the work presented in the study, highlighting what has been achieved and noteworthy findings. Section 7.2 comments on future research ideas that could potentially extend the work produced in this study.

7.1 Summary

There were two main objectives laid out in the very beginning of the thesis. The first objective was to study and define a co-evolutionary particle swarm optimisation (CEPSO) model that could be used to optimise a neural network to detect trend reversals, which could be utilised for security trading purposes. The second objective was to examine whether technical market indicators could provide sufficient information to derive intelligent trading models using historical stock price data.

Such a model was defined and applied to eight company stock prices. The model was executed for different configurations, allowing the model's exploration ability to be investigated and iteratively improved. Four different technical market indicators were used to transform the security prices and provided the necessary market-related

data to the model.

The discovered strategies reflected high profitability and low risk when they were applied to newly introduced data not used for training. The solutions were compared against two popular benchmarks and successfully outperformed them. The CEPSO agents outperformed a rule-based benchmark by 9.09% and the buy-and-hold strategy by 5.3% in terms of annualised returns. The agents managed to derive correct trade actions successfully from the trend reversal confidence values produced. The configuration that allowed the highest returns consisted of a PSO swarm of 150 particles, using the LBEST topology, four hidden layer neurons and a trend reversal threshold value of $\theta = 0.05$.

Furthermore, other secondary objectives were satisfied in this work. A thorough background study on stock trading, technical market indicators and computational intelligence paradigms was presented, upon which the CEPSO model was built. A competitive fitness function was successfully defined and used as a measure for the relative comparison of discovered strategies. This fitness function allowed solutions to compete and co-evolve within a competitive environment.

7.2 Future Research

Other Technical Market Indicators

Four technical market indicators were considered in this work. A plethora of other indicators could be considered and added to the model. This would be done in an effort to exploit other market properties from security prices in order to improve performance. Chaikin Volatility, Directional Movement Index, Elder Ray, Momentum, Money Flow Index, Parabolic Stop and Reverse, Percentage Bands and Triple Exponential Moving Average are just a few that could be considered.

Using Fundamental Analysis

Adding concepts of fundamental analysis in conjunction with technical analysis could be beneficial. Information could be extracted from financial statements and broker reports and be provided to the agent to be considered together with the technical market indicators.These two analytical methodologies have different advantages and could complement each other if used together. Fundamental analysis favours long-term investments, so it is sensible to state that short-term trading will not benefit with the use of fundamentals. Long-term investments would be the main focus if this task is undertaken.

Neural Network Architectures

Various neural network architectures exist, which might improve the trend reversal confidence returned by the discovered trading agents. A standard feed forward neural network is considered throughout this study, but other architectures such as product unit, functional link, recurrent and time delay neural networks would be worth examining.

PSO Algorithm Variations

A number of variations of the standard PSO algorithm exist. These variations offer improved performance over the standard PSO algorithm that was used in this thesis, that may contribute to better trading agents being discovered. These variations offer better global optimisation of solutions and prevent stagnation on sub optimal solutions.

Deriving Comprehensible Rules

Discovered neural network trading agents can only be used as a black box. It is impossible to understand how the trend reversal confidence is derived from the technical

market indicators. It is not favourable in the financial world to make use of trading models that cannot be explained or understood. Deriving comprehensible rules from neural network agents would be desirable, since a better understanding of the trading strategy would make it more forthcoming. Additionally, comprehending discovered strategies could help define better rules for deriving trading actions from the trend reversal confidence, or even improve neural network configuration.

Defining PSO constraints

PSO solution constraints could be defined to control further the quality of the returned strategies. For example, constraints applied to average trade length of solutions could be used to define the term length of discovered solutions. Another constraint could be placed on the number of trades the strategy produces, in order to define the trading frequency. If low frequency trading is desired, an upper limit to the number of trades could be placed that would force a smaller number of trades per strategy.

Other Competitive Fitness Functions

The performance of the model could be improved by introducing different performance metrics to the competitive fitness function. Measures such as maximum draw down, internal rate of return and net present value could be considered. Furthermore, different fitness functions could be considered altogether. A different competitive fitness function may offer a better relative performance evaluation, contributing to a better co-evolutionary environment.

Finding Multiple Solutions via Niching

The problem of convergence on sub-optimal solutions could further be addressed using PSO niching. Niching would allow multiple solutions to be explored synchronously

during training, increasing the probability of discovering global minima.

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Appendices

Appendix A

Symbols and Abbreviations

Abbreviation	Description	Definition
AN	Artificial Neuron	page 35
ANN	Artificial Neural Network	page 35
BAH	Buy And Hold	page 87
BPS	Basis Points	page 64
CEPSO	Co-Evolutionary Particle Swarm Optimisation	page 58
CI	Computational Intelligence	page 34
EC	Evolutionary Computation	page 42
EMA	Exponential Moving Average	page 27
EMH	Efficient Market Hypothesis	page 15
FFNN	Feed Forward Neural Networks	page 37
GA	Genetic Algorithms	page 42
GBEST	Global Best Topology	page 46
GBP	British Pound	page 76
GD	Gradient Descent	page 40
GP	Genetic Programming	page 42
LBEST	Local Best Topology	page 47
LVQ	Learning Vector Quantizer	page 40

Abbreviation	Description	Definition
MACD	Moving Average Convergence/Divergence	page 27
P&L	Profit and Loss	page 67
PSO	Particle Swarm Optimisation	page 44
RSI	Relative Strength Index	page 30
SR	Sharpe Ratio	page 68
SOM	Self Organising Maps	page 40
TA	Technical Analysis	page 13
TMI	Technical Market Indicator	page 18
USD	US Dollar	page 76
VWAP	Volume Weighted Average Price	page 19

Appendix B

Financial Glossary

aroon: A technical market indicator introduced by Tushar S. Chande [24]. The indicator attempts to quickly detect trend reversals and trend strengths. It measures the number of time periods within a predefined time window frame, since the most recent high price and low price. The main assumption this indicator makes is that a security price will close at a high for the given period in an up-trend, and at a low for the given period in a down-trend. Refer to chapter 3.

asset: A resource having economic value that an individual, corporation or country owns or controls with the expectation that it will provide future benefit.

basis point: A basis point is 1/100th of a percentage point, or 0.01%. It is used as a unit of measure in finance.

bear market: A market condition in which prices of securities are falling or are expected to fall. A lack of confidence surrounds such market conditions. The opposite market condition is described as a bull market.

Bollinger bands: A technical market indicator created by John A. Bollinger [19]. It addresses the issue of dynamic volatility by introducing adaptive bands that widen during periods of high volatility and contract during periods of low volatility. Bollinger Bands' main purpose is to place the current price of a security into perspective, pro-

viding a relative definition of high and low.

bond: A bond is a fixed interest financial asset, usually issued by the government or large corporations. Bonds do not represent ownership, but rather a debt agreement. An investor who buys a bond is actually lending capital to the issuer and fixed amounts get paid back to the investor on specific end dates.

bubble: A temporary market condition created through excessive buying, resulting in the dramatic increase of stock prices. Typically, these bubbles are followed by even faster price drops due to sell-offs, which are referred to as a burst.

bull market: A market condition in which prices of securities are rising or are expected to rise. Bull markets are characterized by optimism by investors. High confidence and expectations surround the market that strong results will continue. The opposite market condition is described as a bear market.

buy-and-hold strategy: A passive investment strategy in which an investor buys securities and holds them for a long period, regardless of fluctuations in the market. An investor who employs a buy-and-hold strategy, selects favourable securities and invests in them indefinitely. This strategy is not concerned with short-term price movements and technical indicators.

capital gain/loss: Capital gain is an increase in the value of an asset, giving it higher worth than the purchase price. Capital loss entails the exact opposite, where there is a decrease in the value of an asset.

Chaikin volatility: This is a technical market indicator introduced by Marc Chaikin [31]. It attempts to determine the volatility of a given security by calculating percentage changes in the moving average of the high and low prices. Volatility is quantified as a widening of the range between the two moving averages, hence larger percentage values.

common stock: Refer to the definition of ordinary shares.

credit crunch: A credit crunch is a sudden reduction in the availability of loans/credit

or a sudden increase in the cost of obtaining a loan from financial institutions.

daily trend: A market trend that takes place within a single trading day.

demand: A consumer's desire or willingness to pay for a good or service.

derivatives: These are financial instruments, like options and futures contracts, that derive their value by reference to an underlying asset or index.

directional movement index: A technical market indicator created by J. Welles Wilder [162]. This indicator is used to identify when a definable trend is present in a security. The indicator defines two time series, one to highlight positive (upward) movement or buying pressure and other to measures negative (downward) movement, reflecting selling pressure.

efficient market hypothesis: An investment theory that states that it is impossible to beat the market because stock market efficiency means that existing share prices always incorporate and reflect all relevant information.

Elder ray: A technical market indicator developed by Dr Alexander Elder [47], used to measure buying and selling pressures in the market. This indicator is composed of two time series, one referred to as bull power and the other as bear power.

equity: Refer to the definition of stock.

executing broker: The broker or dealer that finalises and processes an order on behalf of a client. Orders are sent to the broker and assessed for appropriateness. In the case that an order is deemed practical, the executing broker will then carry out the order.

FT global 500: An annual snapshot of the largest 500 companies worldwide, ranked by market capitalisation. The intention is to highlight how corporate fortunes change over time in different countries and industries. The list is maintained by the Financial Times [154].

fundamental analysis: This involves the analysis of the company's income sheets, financial statements, management, company strategy, and generally any fundamental

information about the company itself. Companies are generally valued based on all fundamental data and if a company is discovered to be either undervalued or overvalued, company stocks are bought or sold respectively.

hedge fund: A pooled investment fund, usually a private partnership, that seeks to maximise absolute returns using a broad range of strategies.

index: An aggregate value produced by combining several stocks or other investment vehicles together. Market indexes are intended to represent an entire stock market or a sector and thus track the market's changes over time.

internal rate of return: The internal rate of return is a capital budgeting metric used in finance to decide whether investments should be made. It is an indicator of the efficiency of an investment. It is an annualised effective compounded return rate that can be earned on the invested capital.

investor: An individual who commits money to investment products with the expectation of financial return. Generally, the primary concern of an investor is to minimise risk while maximising return.

limited liability: A concept whereby a person's financial liability is limited to a fixed sum - most commonly, the value of their investment in a company or partnership.

liquidity: Describes the level to which a security can be traded without significantly affecting price. A liquid security can undergo a high volume of trading without a significant change in price.

market capitalisation: A measurement of wealth or economic size of a public company. It is calculated by multiplying the number of outstanding shares times the current market price per share of the company.

market cycle: The period between two bull or bear markets.

market momentum indicator: The market momentum indicator is a calculation of the difference between the current market price of a security and the price of the same security a certain number of prior periods ago.

market volatility: This is the pace at which a security price moves higher and lower. If the price of a security moves up and down rapidly over short time periods, it has high volatility. If the price almost never changes, it has low volatility. If a security is more volatile, it is also more risky.

maximum drawdown: The maximum drawdown is the maximum loss that a trading strategy has incurred in the past. From the maximum drawdown one can derive a maximum drawdown period and maximum drawdown rate, which indicates the amount of time and the number of trades required by the strategy to recover such a loss. These risk measures are used to highlight the consequences of the worst case loss scenario and how the strategy handles the scenario.

money flow index: The money flow index is a technical market indicator used to determine the momentum in a trend by analysing the price and volume of a given security. This is done by calculating the strength of money going in and out of a security and can be used to predict trend reversal.

moving average divergence/convergence: A technical market indicator developed by Gerald Appel[7] as a stock market timing device, utilising market momentum and trend. It is used by traders to determine when to buy or sell a security, based on the interaction between a line constructed from two exponential moving averages and a trigger line.

net present value: Net present value is the present value of future cash in-flows minus the cost including cost of investment, calculated using an appropriate discounting method.

ordinary share: The most common class of share representing the owners interest in a company. It entitles the owner to a share of the corporation's profits and a share of the voting power in shareholder elections

parabolic stop and reverse: A technical market indicator by J. Welles Wilder [162]. This indicator utilises a trailing stop and reverse method to determine good trade

exit and entry points.

perpetual claim: One of the characteristics of ordinary shares that allows individual shareholders to liquidate their investments in the share of a company. This can only by done by selling them to another investor.

primary trend: A primary trend consists of long-term price movements, usually a month or longer.

profit and loss: The calculation of net profit on trading less fixed costs, such as transaction costs.

return on investment: Refer to returns.

relative momentum index: One of the many technical market indicators introduced by J. Welles Wilder. This indicator returns a tracking value of the price strength and ultimately displays the velocity and momentum of a security price. This is done by comparing the magnitude of a security's recent gains to the magnitude of its recent losses.

returns: The annual return on an investment, expressed as a percentage of the total amount invested.

residual claim: Ordinary shareholders have a claim on the income and net assets of the company after obligations to creditors, bond holders and preferred shareholders have been met.

retracement: A reverse movement of the price or its rollback from the previous maximum or minimum. This is generally a price movement in the opposite direction of the previous trend.

risk: The quantifiable likelihood of loss or less-than-expected returns. It is the chance that an investment's actual return will be different than the one expected. It is usually measured using the historical returns or average returns for a specific security.

risk-free rate: The theoretical return attributed to an investment with zero risk. The risk-free rate represents the interest on an investor's money that is to be expected

from an absolutely risk-free investment over a specified period of time.

script lending: Script lending enables investors to borrow shares that they do not own and then sell them to other market participants. The borrower pays a fee for the service and is obliged to return the borrowed shares back to the owner upon request.

secondary trend: A secondary trend consists of price movements up to a month in length.

security: An investment instrument issued by a corporation, government, or other organization that offers evidence of debt or equity.

sentiment: A thought, view, or attitude of specialists as to the future direction of a security or of the stock market itself.

share: Refer to the definition of stock.

Sharpe ratio: A ratio developed by Bill Sharpe to measure risk-adjusted performance. It is calculated by subtracting the risk free rate from the rate of return for a portfolio or security and dividing the result by the standard deviation of the returns.

short sell: refer to script lending.

stock: An instrument that signifies an ownership position in a corporation, and represents a claim on its proportional share in the corporation's assets and profits.

stock dividends: A dividend is a share of a company's profits that it pays to investors. Profits are not always divided to shareholders via dividends, it is common for earnings to be retained and reinvested into the company.

stock market: A stock market represents the mechanism of organised trading of securities. Stock markets allow buyers and sellers to get together and participate in the exchange of securities in an efficient manner, while obeying certain rules and regulations.

supply: The total amount of a good or services available for purchase at a certain price.

technical analysis: Technical analysis is a technique where historic data primarily

price and volume, is used to identify past trends and behaviour in tradable market products. By understanding how these products have functioned in the past, technical traders attempt to utilise gained knowledge to forecast future price movements that will enable them to enter and exit trades at the right time in order to realise a profit.

technical market indicator: A time series that is derived from applying a mathematical formula to the price data of a specific security. The indicator exposes certain properties and behaviour that usually is not clear by inspecting the price only. Such properties and behaviour provides a unique perspective on the strength and direction of the underlying security's future price.

trend: A long-term general movement direction or change in frequency of a security price.

triple exponential moving average: A technical market indicator that attempts to highlight momentum, displayed as an oscillator above and below a zero line. It compares two triple smoothed exponential moving averages, and displays the difference as a single line with positive and negative values.

volume: The number of shares or contracts traded in a security or an entire market during a given period of time. It is simply the amount of shares that trade hands from sellers to buyers as a measure of activity.

volume weighted average price: The volume weighted average price is the average price at which a stock trades in a given period, weighted by the volume traded at each price.

Appendix C

Stock Price Graphs

This appendix illustrates the price graphs of all eight stocks that were selected for the experimental results for this thesis. The stocks were selected based on top market capitalisation, as defined by the *FT Global 500* [154]. The top four US and top four UK companies were chosen using the capitalisation list published on the 31st March 2008. Table C.1 lists the stocks, together with their corresponding worldwide rank, country, currency, industry and market capitalisation.

Table C.1: Stock selection for empirical study.

Rank	Name	Country	Currency	Industry	Market Capital (USD million)
1	Exxon Mobil	US	USD	Oil and Gas	452,505
3	General Electric	US	USD	Conglomerate	369,569
7	Microsoft	US	USD	Software Industry	264,132
8	AT&T	US	USD	Telecommunications	231,168
15	HSBC	UK	GBP	Banking	195,768
16	BP	UK	GBP	Oil and Gas	191,844
28	Vodafone	UK	GBP	Telecommunications	159,553
30	Rio Tinto Group	UK	GBP	Mining	154,860

Figure C.1: Exxon Mobil stock price(USD)

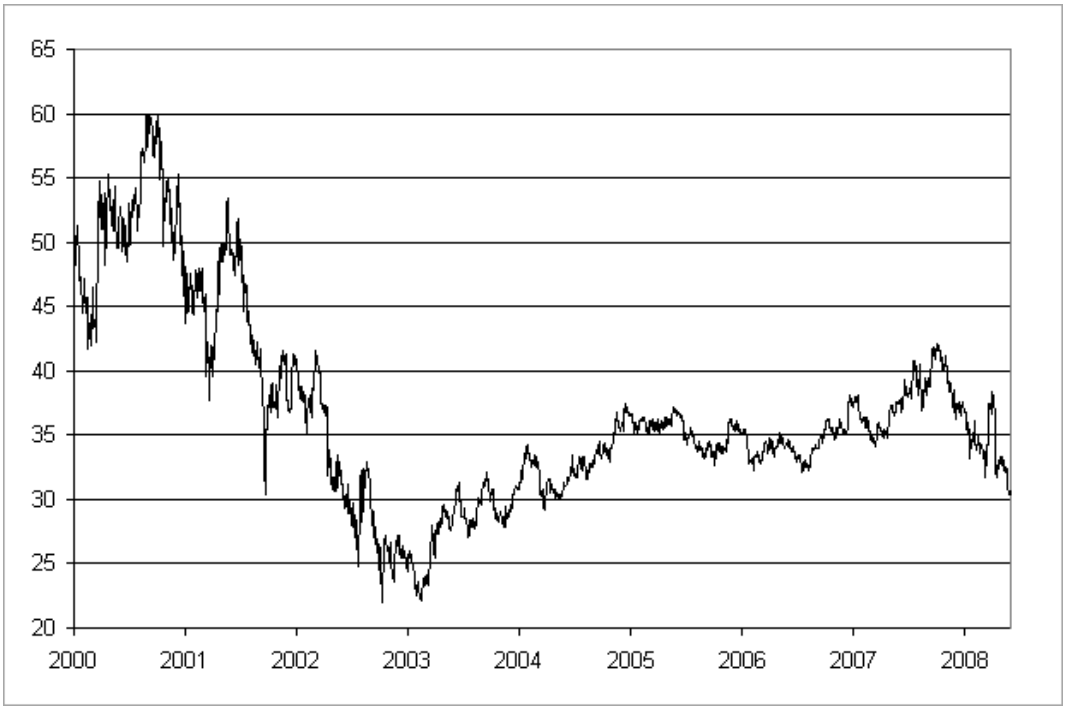

Figure C.2: General Electric stock price(USD)

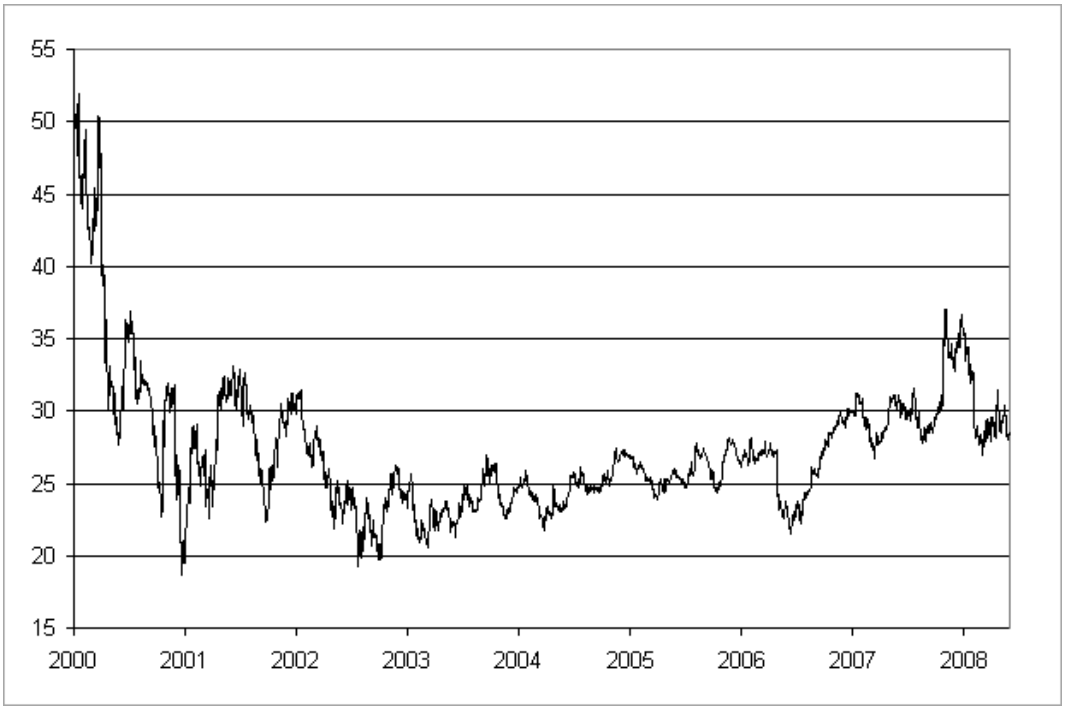

Figure C.3: Microsoft stock price(USD)

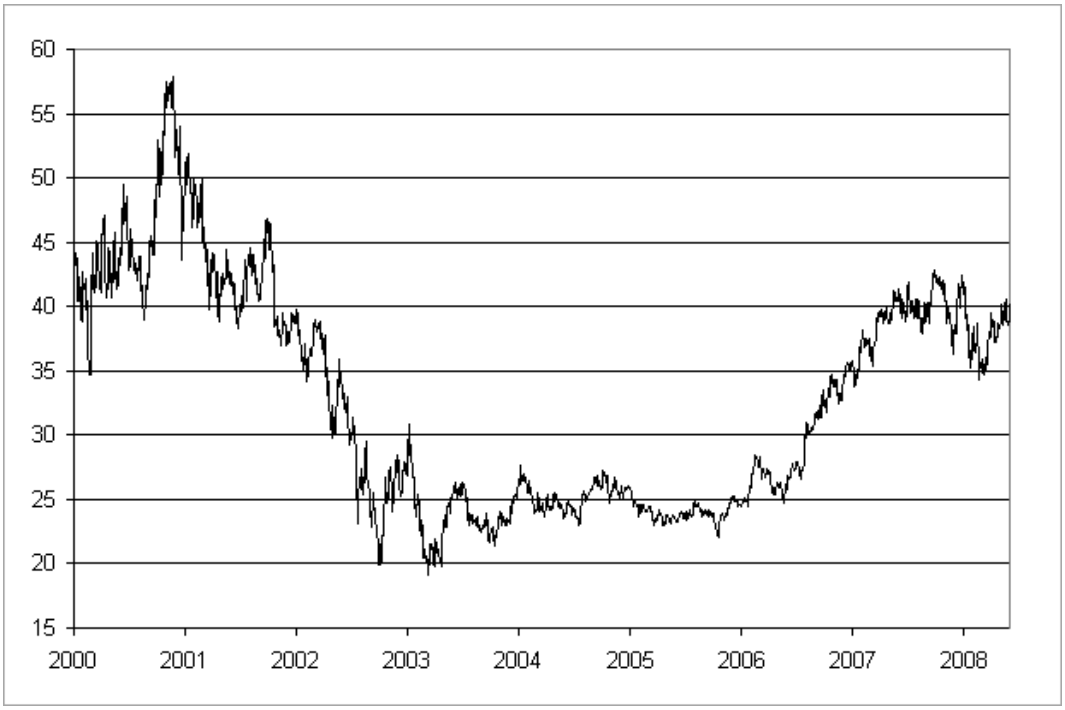

Figure C.4: AT&T stock price(USD)

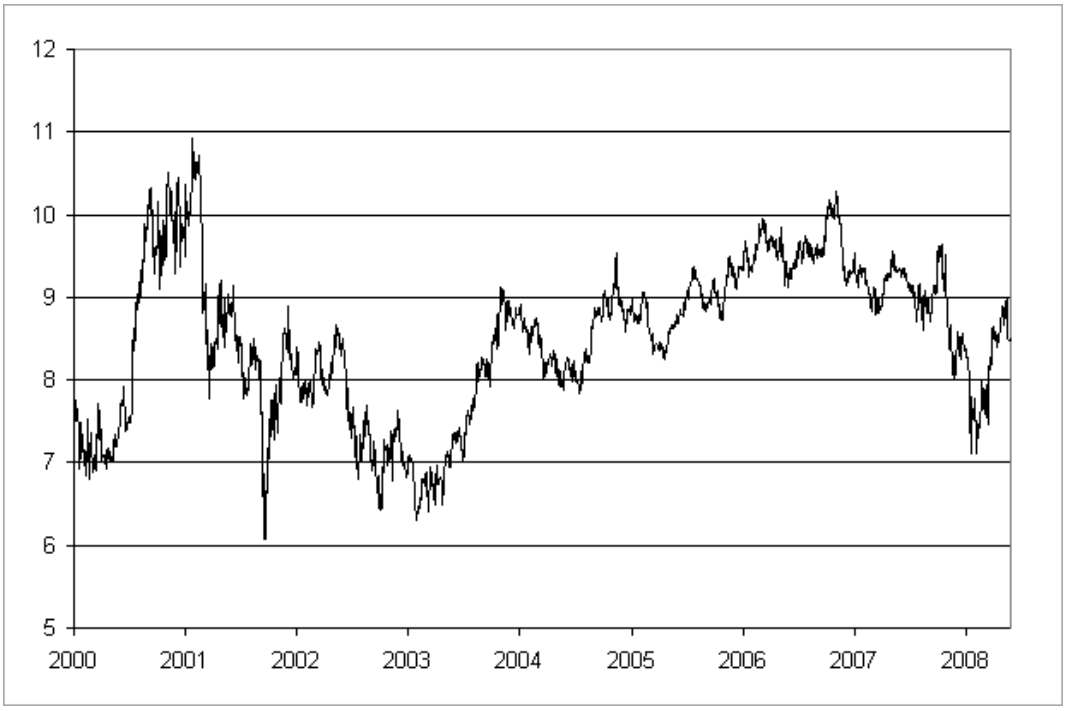

Figure C.5: HSBC stock price(GBP)

Figure C.6: BP stock price(GBP)

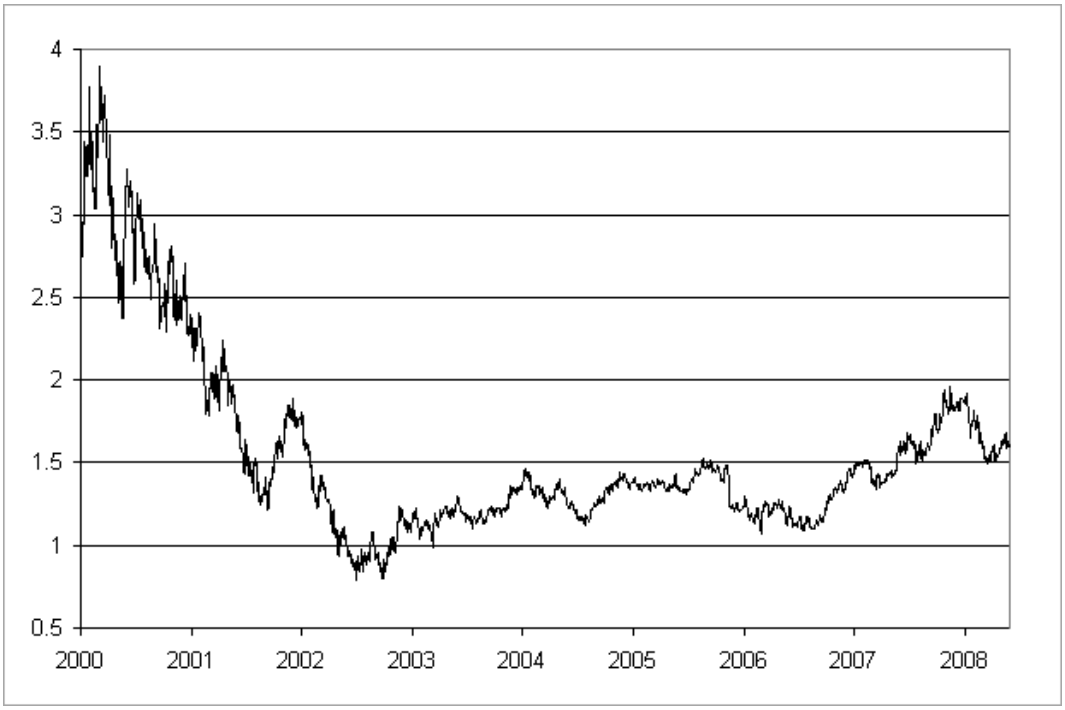

Figure C.7: Vodafone stock price(GBP)

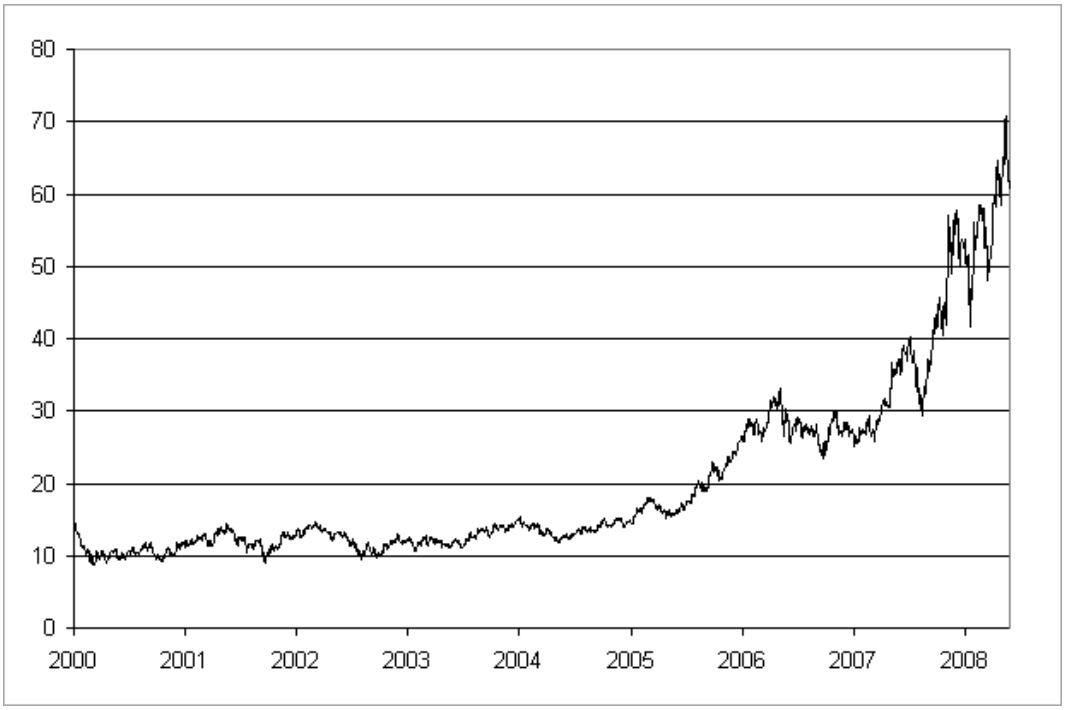

Figure C.8: Rio Tinto Group stock price(GBP)

Appendix D

Empirical Study Tables

The tables in this appendix depict the empirical results for the investigated competitive CEPSO model. Different tables depict results for different experiments. All tables follow the exact same layout.

All tables display the different parameter combinations, which are indicated on the top row and left most column of each table. The top half of each table lists the averages for the simulated runs, while the bottom half list the standard deviations. The left half lists the in-sample results, while the right half lists the out-sample results. The averages of the average and standard deviation results are indicated in the last column and row of each table.

Table D.1: Annualised returns (%) for the GBEST topology

		Hidden Neurons (In-Sample)						Hidden Neurons (Out-Sample)					
	Particles	2	4	6	8	10	Avg	2	4	6	8	10	Avg
Returns(Avg)	10	14.42	16.84	21.48	22.72	23.47	19.78	5.57	8.03	7.65	9.1	9.15	7.9
	25	19.64	22.41	26.05	27.5	26.55	24.43	6.96	8.44	8.37	9.02	9.8	8.52
	50	22.15	25.87	29.46	29.6	29.82	27.38	7.73	8.65	9.14	9.29	**10.34**	9.03
	100	23.59	28.23	31.16	32.34	31.81	29.43	7.27	8.78	8.85	9.3	8.76	8.59
	150	25.0	29.9	33.11	33.27	33.77	31.01	6.39	8.08	8.9	9.34	9.95	8.53
	200	26.56	30.83	33.28	35.49	34.32	32.09	6.33	7.04	9.29	8.16	10.3	8.23
	Avg	21.89	25.68	29.09	30.15	29.96		6.71	8.17	8.7	9.04	9.72	
Returns(Std)	10	7.65	8.54	9.11	8.36	8.81	8.49	13.5	14.83	11.97	13.51	12.96	13.36
	25	9.7	8.96	9.14	9.27	9.42	9.3	12.42	12.1	11.69	11.89	12.34	12.09
	50	10.03	9.74	9.36	9.29	10.67	9.82	13.12	12.32	12.27	11.79	12.32	12.36
	100	9.57	9.66	9.42	9.95	10.64	9.85	11.31	13.03	13.8	12.28	11.53	12.39
	150	9.44	9.58	9.92	10.28	10.29	9.9	11.39	13.21	13.48	12.83	11.83	12.55
	200	11.19	10.28	9.62	9.27	9.82	10.04	12.64	11.62	12.74	10.48	12.28	11.95
	Avg	9.6	9.46	9.43	9.4	9.94		12.4	12.85	12.66	12.13	12.21	

Table D.2: Annualised returns (%) for the Von Neumann topology

		Hidden Neurons (In-Sample)						Hidden Neurons (Out-Sample)					
	Particles	2	4	6	8	10	Avg	2	4	6	8	10	Avg
Returns(Avg)	10	18.39	21.55	22.6	21.32	21.12	21.0	8.95	9.7	10.26	9.43	10.55	9.78
	25	23.17	24.55	24.18	23.65	22.82	23.67	10.74	9.93	10.08	10.52	10.0	10.25
	50	24.92	26.0	27.07	25.73	25.41	25.83	10.97	11.22	10.85	12.19	11.5	11.35
	100	26.54	27.05	28.41	27.84	27.13	27.39	11.45	11.55	10.98	11.42	9.63	11.0
	150	26.28	28.05	28.99	29.68	28.96	28.39	12.21	11.07	10.84	11.38	10.26	11.15
	200	26.38	28.53	29.25	28.94	29.59	28.54	**13.35**	10.86	11.3	11.1	10.17	11.36
	Avg	24.28	25.95	26.75	26.19	25.84		11.28	10.72	10.72	11.01	10.35	
Returns(Std)	10	9.08	8.3	8.13	8.15	8.18	8.37	14.33	12.35	13.47	11.37	12.2	12.74
	25	8.14	8.01	8.39	8.76	8.63	8.39	14.6	13.48	12.6	13.13	11.81	13.13
	50	8.31	8.26	8.5	9.01	9.2	8.65	14.46	13.82	13.89	13.53	12.87	13.71
	100	8.47	8.23	8.41	8.82	9.12	8.61	15.11	14.15	14.27	13.34	13.02	13.98
	150	8.11	8.43	9.1	8.7	9.09	8.68	15.21	13.46	13.2	13.77	12.06	13.54
	200	8.29	8.76	8.64	8.95	9.46	8.82	16.11	13.63	14.5	13.64	12.29	14.03
	Avg	8.4	8.33	8.53	8.73	8.95		14.97	13.48	13.66	13.13	12.38	

Table D.3: Annualised returns (%) for the LBEST topology

		Hidden Neurons (In-Sample)						Hidden Neurons (Out-Sample)					
	Particles	2	4	6	8	10	Avg	2	4	6	8	10	Avg
Returns(Avg)	10	19.21	21.84	23.17	23.84	22.52	22.11	9.67	9.58	10.14	10.42	9.35	9.83
	25	22.81	24.59	25.94	25.65	26.41	25.08	9.54	10.57	11.17	10.75	9.78	10.36
	50	24.87	25.77	27.28	27.81	28.2	26.79	11.18	11.21	11.16	11.73	10.26	11.11
	100	25.91	27.23	28.49	28.26	29.19	27.82	12.19	10.68	11.42	11.96	11.22	11.49
	150	26.51	27.31	28.85	29.29	29.37	28.27	12.61	**13.21**	11.37	11.43	10.99	11.92
	200	27.19	27.92	29.35	29.67	29.9	28.8	12.98	12.21	**13.14**	10.83	12.98	12.43
	Avg	24.42	25.77	27.18	27.42	27.6		11.36	11.24	11.4	11.19	10.76	
Returns(Std)	10	7.87	7.53	7.63	7.71	8.2	7.79	13.12	13.36	13.52	13.62	11.2	12.96
	25	7.45	8.0	7.95	7.53	8.46	7.88	12.03	12.99	12.5	12.42	11.37	12.26
	50	8.25	7.83	8.32	7.81	8.67	8.18	13.72	13.29	12.27	14.12	12.61	13.2
	100	7.68	8.37	8.0	8.0	8.18	8.05	14.88	12.63	12.11	12.96	13.63	13.24
	150	7.69	8.27	8.23	8.82	8.47	8.3	14.14	15.38	12.5	13.45	12.45	13.59
	200	8.28	8.18	8.1	7.88	8.2	8.13	13.86	15.24	14.14	11.61	14.62	13.89
	Avg	7.87	8.03	8.04	7.96	8.36		13.62	13.82	12.84	13.03	12.65	

Table D.4: Profit and loss (x100000) for the GBEST topology

		Hidden Neurons (In-Sample)						Hidden Neurons (Out-Sample)					
	Particles	2	4	6	8	10	Avg	2	4	6	8	10	Avg
P&L(Avg)	10	8.68	10.1	12.89	13.64	14.08	11.88	1.12	1.61	1.53	1.82	1.83	1.58
	25	11.79	13.45	15.64	16.5	15.92	14.66	1.39	1.68	1.67	1.81	1.96	1.7
	50	13.28	15.55	17.69	17.78	17.9	16.44	1.55	1.73	1.82	1.87	**2.07**	1.81
	100	14.16	16.94	18.71	19.42	19.1	17.67	1.45	1.76	1.78	1.87	1.75	1.72
	150	15.01	17.96	19.89	19.98	20.28	18.62	1.27	1.62	1.78	1.87	1.99	1.71
	200	15.94	18.51	19.98	21.32	20.6	19.27	1.26	1.41	1.86	1.63	2.06	1.65
	Avg	13.14	15.42	17.47	18.1	17.98		1.34	1.63	1.74	1.81	1.94	
P&L(Std)	10	4.58	5.13	5.47	5.03	5.29	5.1	2.71	2.97	2.39	2.7	2.59	2.67
	25	5.83	5.36	5.49	5.55	5.67	5.58	2.48	2.43	2.34	2.38	2.47	2.42
	50	6.02	5.84	5.6	5.58	6.41	5.89	2.62	2.46	2.46	2.36	2.46	2.47
	100	5.75	5.81	5.66	5.97	6.38	5.92	2.27	2.61	2.76	2.46	2.31	2.48
	150	5.68	5.77	5.98	6.19	6.18	5.96	2.28	2.64	2.7	2.57	2.36	2.51
	200	6.71	6.15	5.76	5.58	5.89	6.02	2.53	2.32	2.54	2.09	2.46	2.39
	Avg	5.76	5.68	5.66	5.65	5.97		2.48	2.57	2.53	2.42	2.44	

Table D.5: Profit and loss (x100000) for the Von Neumann topology

		Hidden Neurons (In-Sample)						Hidden Neurons (Out-Sample)					
	Particles	2	4	6	8	10	Avg	2	4	6	8	10	Avg
P&L(Avg)	10	11.05	12.92	13.57	12.78	12.68	12.6	1.8	1.95	2.05	1.88	2.11	1.96
	25	13.92	14.74	14.54	14.2	13.7	14.22	2.15	1.99	2.02	2.1	2.0	2.05
	50	14.95	15.62	16.25	15.44	15.25	15.5	2.2	2.24	2.18	2.44	2.3	2.27
	100	15.94	16.23	17.03	16.74	16.29	16.44	2.29	2.31	2.2	2.29	1.92	2.2
	150	15.78	16.85	17.39	17.83	17.39	17.05	**2.45**	2.21	2.17	2.27	2.06	2.23
	200	15.85	17.15	17.55	17.39	17.77	17.14	**2.67**	2.17	2.26	2.22	2.03	2.27
	Avg	14.58	15.59	16.05	15.73	15.51		2.26	2.14	2.15	2.2	2.07	
P&L(Std)	10	5.45	5.0	4.89	4.91	4.92	5.03	2.87	2.47	2.7	2.28	2.44	2.55
	25	4.87	4.81	5.02	5.23	5.16	5.02	2.93	2.7	2.52	2.63	2.37	2.63
	50	4.99	4.97	5.09	5.4	5.51	5.19	2.9	2.77	2.78	2.71	2.57	2.74
	100	5.07	4.94	5.06	5.3	5.49	5.17	3.02	2.83	2.86	2.67	2.6	2.8
	150	4.87	5.07	5.47	5.22	5.46	5.22	3.05	2.7	2.64	2.76	2.41	2.71
	200	4.99	5.27	5.18	5.36	5.65	5.29	3.22	2.73	2.9	2.72	2.46	2.81
	Avg	5.04	5.01	5.12	5.24	5.37		3.0	2.7	2.73	2.63	2.47	

Table D.6: Profit and loss (x100000) for the LBEST topology

		Hidden Neurons (In-Sample)						Hidden Neurons (Out-Sample)					
	Particles	2	4	6	8	10	Avg	2	4	6	8	10	Avg
P&L(Avg)	10	11.55	13.11	13.9	14.32	13.52	13.28	1.93	1.92	2.03	2.08	1.88	1.97
	25	13.69	14.74	15.55	15.4	15.86	15.05	1.91	2.12	2.24	2.15	1.96	2.07
	50	14.95	15.46	16.38	16.71	16.92	16.08	2.24	2.24	2.23	2.35	2.06	2.22
	100	15.55	16.36	17.12	16.98	17.54	16.71	2.44	2.14	2.29	2.39	2.25	2.3
	150	15.92	16.38	17.32	17.59	17.64	16.97	2.52	**2.64**	2.27	2.29	2.2	2.39
	200	16.32	16.76	17.61	17.8	17.95	17.29	2.59	2.44	**2.63**	2.17	2.6	2.48
	Avg	14.66	15.47	16.31	16.47	16.57		2.27	2.25	2.28	2.24	2.16	
P&L(Std)	10	4.73	4.51	4.57	4.63	4.92	4.67	2.62	2.67	2.7	2.72	2.24	2.59
	25	4.46	4.82	4.75	4.51	5.1	4.73	2.4	2.6	2.5	2.49	2.28	2.45
	50	4.96	4.7	4.99	4.67	5.18	4.9	2.75	2.66	2.46	2.82	2.52	2.64
	100	4.63	5.01	4.8	4.8	4.89	4.83	2.97	2.53	2.42	2.59	2.73	2.65
	150	4.63	4.96	4.93	5.27	5.09	4.98	2.83	3.08	2.5	2.69	2.5	2.72
	200	4.97	4.92	4.87	4.73	4.92	4.88	2.78	3.05	2.83	2.33	2.92	2.78
	Avg	4.73	4.82	4.82	4.77	5.02		2.72	2.77	2.57	2.61	2.53	

Table D.7: Sharpe ratio for the GBEST topology

		Hidden Neurons (In-Sample)						Hidden Neurons (Out-Sample)					
	Particles	2	4	6	8	10	Avg	2	4	6	8	10	Avg
Sharpe(Avg)	10	0.53	0.68	0.97	1.04	1.05	0.85	0.05	0.1	0.17	0.23	0.21	0.15
	25	0.85	1.05	1.25	1.33	1.28	1.15	0.12	0.2	0.21	0.27	0.23	0.21
	50	1.01	1.25	1.46	1.45	1.45	1.32	0.11	0.2	0.27	0.3	**0.37**	0.25
	100	1.15	1.4	1.59	1.64	1.62	1.48	0.13	0.22	0.22	0.3	0.26	0.23
	150	1.24	1.47	1.68	1.72	1.73	1.57	0.02	0.19	0.17	0.32	**0.37**	0.21
	200	1.29	1.56	1.73	1.81	1.77	1.63	-0.01	0.13	0.26	0.21	0.36	0.19
	Avg	1.01	1.23	1.45	1.5	1.48		0.07	0.17	0.22	0.27	0.3	
Sharpe(Std)	10	0.39	0.45	0.41	0.37	0.38	0.4	0.58	0.85	0.64	0.66	0.92	0.73
	25	0.5	0.45	0.36	0.34	0.35	0.4	0.59	0.63	0.61	0.61	1.09	0.71
	50	0.5	0.44	0.36	0.34	0.39	0.41	0.71	0.69	0.63	0.69	0.77	0.7
	100	0.48	0.38	0.35	0.37	0.39	0.39	0.69	0.61	0.66	0.66	0.82	0.69
	150	0.47	0.4	0.36	0.39	0.38	0.4	1.12	0.64	1.11	0.69	0.61	0.84
	200	0.49	0.37	0.36	0.35	0.4	0.39	0.98	0.65	0.63	0.84	0.71	0.76
	Avg	0.47	0.41	0.36	0.36	0.38		0.78	0.68	0.71	0.69	0.82	

Table D.8: Sharpe ratio for the Von Neumann topology

		Hidden Neurons (In-Sample)						Hidden Neurons (Out-Sample)					
	Particles	2	4	6	8	10	Avg	2	4	6	8	10	Avg
Sharpe(Avg)	10	0.79	0.98	1.05	0.99	0.97	0.96	0.15	0.26	0.33	0.31	0.38	0.29
	25	1.09	1.19	1.17	1.11	1.07	1.12	0.28	0.27	0.29	0.36	0.36	0.31
	50	1.17	1.26	1.3	1.22	1.19	1.23	0.33	0.38	0.36	**0.46**	0.44	0.39
	100	1.27	1.32	1.38	1.34	1.31	1.32	0.19	0.41	0.27	0.43	0.26	0.31
	150	1.28	1.36	1.41	1.41	1.4	1.37	0.4	0.32	0.4	0.43	0.4	0.39
	200	1.3	1.4	1.44	1.43	1.42	1.4	**0.45**	0.35	0.39	0.39	0.36	0.39
	Avg	1.15	1.25	1.29	1.25	1.22		0.3	0.33	0.34	0.4	0.37	
Sharpe(Std)	10	0.41	0.32	0.29	0.32	0.32	0.33	1.51	0.69	0.73	0.64	0.62	0.84
	25	0.25	0.23	0.3	0.33	0.35	0.29	0.91	0.76	0.74	0.69	0.71	0.76
	50	0.24	0.25	0.29	0.31	0.33	0.28	0.63	0.66	0.65	0.63	0.64	0.64
	100	0.23	0.25	0.24	0.27	0.31	0.26	2.65	0.66	1.46	0.62	0.8	1.24
	150	0.23	0.26	0.28	0.27	0.33	0.27	0.69	1.07	0.64	0.62	0.68	0.74
	200	0.23	0.24	0.26	0.27	0.32	0.26	0.67	0.68	0.68	0.63	0.62	0.65
	Avg	0.27	0.26	0.28	0.29	0.33		1.18	0.75	0.81	0.64	0.68	

Table D.9: Sharpe ratio for the LBEST topology

		Hidden Neurons (In-Sample)						Hidden Neurons (Out-Sample)					
	Particles	2	4	6	8	10	Avg	2	4	6	8	10	Avg
Sharpe(Avg)	10	0.83	0.97	1.07	1.06	1.05	1.0	0.26	0.23	0.24	0.32	0.3	0.27
	25	1.07	1.15	1.21	1.24	1.24	1.18	0.26	0.34	0.41	0.38	0.34	0.35
	50	1.17	1.24	1.3	1.33	1.33	1.27	0.4	0.41	0.42	0.42	0.39	0.41
	100	1.25	1.32	1.38	1.39	1.42	1.35	0.42	0.37	0.43	0.41	0.4	0.41
	150	1.26	1.33	1.4	1.42	1.43	1.37	0.45	**0.49**	0.43	0.45	0.28	0.42
	200	1.29	1.35	1.41	1.46	1.46	1.39	0.47	0.41	**0.55**	0.42	**0.49**	0.47
	Avg	1.14	1.23	1.29	1.31	1.32		0.38	0.38	0.41	0.4	0.37	
Sharpe(Std)	10	0.33	0.29	0.29	0.28	0.29	0.3	0.65	0.68	1.02	0.62	0.66	0.73
	25	0.25	0.27	0.26	0.25	0.29	0.26	0.63	0.63	0.59	0.62	0.72	0.64
	50	0.25	0.24	0.25	0.25	0.27	0.25	0.67	0.67	0.63	0.63	0.63	0.65
	100	0.24	0.25	0.23	0.24	0.27	0.24	0.7	0.64	0.62	1.07	0.64	0.73
	150	0.23	0.23	0.23	0.24	0.25	0.24	0.62	0.66	0.73	0.63	2.04	0.94
	200	0.23	0.23	0.24	0.25	0.25	0.24	0.82	0.85	0.7	0.61	0.84	0.76
	Avg	0.26	0.25	0.25	0.25	0.27		0.68	0.69	0.71	0.7	0.92	

Table D.10: Annualised returns (%) for the favourite LBEST and Von Neumann topologies

	Company	Topology (In-Sample) LBEST	V NEUM	Avg	Topology (Out-Sample) LBEST	V NEUM	Avg
Returns(Avg)	Exxon Mobil	21.6	20.53	21.07	16.33	16.53	16.43
	General Electric	18.67	17.5	18.08	6.63	6.6	6.62
	Microsoft	34.47	34.07	34.27	4.3	4.97	4.63
	AT&T	26.5	26.1	26.3	7.23	6.17	6.7
	HSBC	20.57	21.63	21.1	5.23	4.43	4.83
	BP	25.97	24.1	25.03	8.6	8.0	8.3
	Vodafone	31.23	29.33	30.28	10.73	11.23	10.98
	Rio Tinto Group	39.47	37.77	38.62	46.63	48.9	47.77
	Avg	27.31	26.38		13.21	13.35	
Returns(Std)	Exxon Mobil	4.21	4.31	4.26	9.93	8.59	9.26
	General Electric	3.95	5.36	4.66	4.54	4.48	4.51
	Microsoft	5.99	7.87	6.93	7.13	5.45	6.29
	AT&T	5.42	5.45	5.44	8.97	7.36	8.16
	HSBC	3.4	3.1	3.25	6.36	4.53	5.45
	BP	3.2	3.99	3.59	4.76	6.21	5.48
	Vodafone	5.49	4.53	5.01	7.32	4.42	5.87
	Rio Tinto Group	5.52	5.64	5.58	12.63	16.62	14.63
	Avg	4.65	5.03		7.71	7.21	

Table D.11: Profit and loss (x100000) for the favourite LBEST and Von Neumann topologies

	Company	Topology (In-Sample) LBEST	V NEUM	Avg	Topology (Out-Sample) LBEST	V NEUM	Avg
P&L(Avg)	Exxon Mobil	12.96	12.34	12.65	3.27	3.32	3.29
	General Electric	11.18	10.51	10.85	1.31	1.31	1.31
	Microsoft	20.69	20.48	20.59	0.83	1.0	0.92
	AT&T	15.87	15.64	15.76	1.44	1.23	1.33
	HSBC	12.34	12.99	12.66	1.04	0.88	0.96
	BP	15.58	14.53	15.05	1.74	1.6	1.67
	Vodafone	18.71	17.64	18.18	2.17	2.25	2.21
	Rio Tinto Group	23.67	22.65	23.16	9.34	9.77	9.56
	Avg	16.38	15.85		2.64	2.67	
P&L(Std)	Exxon Mobil	2.51	2.57	2.54	1.98	1.73	1.85
	General Electric	2.44	3.25	2.85	0.9	0.9	0.9
	Microsoft	3.57	4.78	4.18	1.44	1.09	1.26
	AT&T	3.25	3.28	3.26	1.8	1.48	1.64
	HSBC	2.01	1.81	1.91	1.27	0.91	1.09
	BP	1.87	2.45	2.16	0.94	1.25	1.09
	Vodafone	3.31	2.7	3.01	1.46	0.88	1.17
	Rio Tinto Group	3.33	3.41	3.37	2.53	3.32	2.93
	Avg	2.79	3.03		1.54	1.45	

Table D.12: Sharpe ratio for the favourite LBEST and Von Neumann topologies

	Company	Topology (In-Sample) LBEST	V NEUM	Avg	Topology (Out-Sample) LBEST	V NEUM	Avg
Sharpe(Avg)	Exxon Mobil	1.36	1.35	1.36	1.02	1.04	1.03
	General Electric	1.34	1.27	1.3	0.53	0.33	0.43
	Microsoft	1.52	1.5	1.51	0.11	0.22	0.17
	AT&T	1.52	1.5	1.51	0.39	0.26	0.33
	HSBC	1.01	1.06	1.03	0.02	-0.07	-0.03
	BP	1.21	1.13	1.17	0.21	0.19	0.2
	Vodafone	1.28	1.28	1.28	0.36	0.42	0.39
	Rio Tinto Group	1.39	1.3	1.34	1.32	1.24	1.28
	Avg	1.33	1.3		0.49	0.45	
Sharpe(Std)	Exxon Mobil	0.21	0.18	0.19	0.57	0.75	0.66
	General Electric	0.17	0.19	0.18	0.47	0.63	0.55
	Microsoft	0.16	0.21	0.18	0.55	0.42	0.49
	AT&T	0.18	0.2	0.19	0.7	0.61	0.66
	HSBC	0.16	0.15	0.15	0.47	0.32	0.4
	BP	0.13	0.2	0.16	0.33	0.55	0.44
	Vodafone	0.19	0.15	0.17	0.52	0.36	0.44
	Rio Tinto Group	0.19	0.18	0.19	0.34	0.46	0.4
	Avg	0.17	0.18		0.49	0.51	

Table D.13: Annualised returns (%) for different reversal confidence thresholds

	Company	Threshold (In-Sample) 0.05	0.1	0.2	0.3	Avg	Threshold (Out-Sample) 0.05	0.1	0.2	0.3	Avg
Returns(Avg)	Exxon Mobil	21.6	24.53	21.24	24.65	23.01	16.33	19.29	16.76	18.29	17.67
	General Electric	18.67	22.71	19.59	20.29	20.32	6.63	6.76	6.88	6.88	6.79
	Microsoft	34.47	31.94	31.71	30.76	32.22	4.3	-0.24	0.41	-0.12	1.09
	AT&T	26.5	27.29	26.35	27.82	26.99	7.23	5.35	8.59	5.29	6.62
	HSBC	20.57	24.53	23.29	22.76	22.79	5.23	1.29	2.29	2.65	2.97
	BP	25.97	26.65	28.19	26.88	26.92	8.6	13.71	10.81	10.94	11.02
	Vodafone	31.23	32.94	34.81	34.63	33.4	10.73	10.44	7.12	8.19	9.12
	Rio Tinto Group	39.47	38.5	41.56	42.13	40.41	46.63	48.13	44.13	34.06	43.24
	Avg	27.31	28.64	28.34	28.74		13.21	13.09	12.13	10.77	
Returns(Std)	Exxon Mobil	4.21	5.12	4.21	3.74	4.32	9.93	9.03	6.36	10.29	8.90
	General Electric	3.95	3.41	4.53	4.12	4.0	4.54	5.09	5.41	5.33	5.09
	Microsoft	5.99	7.31	6.8	7.96	7.02	7.13	6.24	7.67	5.57	6.65
	AT&T	5.42	7.24	6.95	5.33	6.24	8.97	7.8	6.0	7.4	7.54
	HSBC	3.4	3.61	3.57	3.09	3.42	6.36	4.67	8.34	5.37	6.19
	BP	3.2	4.27	2.83	4.01	3.58	4.76	7.14	6.77	9.6	7.07
	Vodafone	5.49	6.23	5.0	5.99	5.68	7.32	9.43	7.75	7.4	7.98
	Rio Tinto Group	5.52	7.51	7.15	7.34	6.88	12.63	13.27	17.76	13.47	14.28
	Avg	4.65	5.59	5.13	5.2		7.71	7.83	8.26	8.05	

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