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Risk Management in the Australian Stockmarket using Artificial Neural Networks

Krollner, Bjoern

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Risk Management in the Australian Stockmarket using Artificial Neural Networks

Bjoern Krollner

A dissertation submitted in total fulfilment of the requirements of the degree of Doctor of Philosophy for the School of Information Technology, Bond University.

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Statement of Original Authorship

This thesis is submitted to Bond University in fulfilment of the requirements of the degree of Doctor of Philosophy. This thesis represents my own original work towards this research degree and contains no material which has been previously submitted for a degree or diploma at this University or any other institution, except where due acknowledgement is made.

Bjoern Krollner

Date

Abstract

This thesis proposes an Artificial Neural Network (ANN) enhanced decision support system for financial risk management. The decision support system allows hedgers to maximise their expected return while practising the hedge against financial risks.

The importance of the research stems from the fact that it can be used to reduce the risk associated with adverse price movements in the stock market.

The literature review reveals that there are a large number of studies trying to forecast movements in the stockmarket, but there is a lack of literature trying to improve stock market risk management strategies with machine learning techniques.

This thesis addresses this gap by applying the existing body of literature in stock index forecasting with machine learning techniques to the domain of portfolio risk management. In particular, it analyses whether strategies used to predict movements in the stock index can also be used to derive hedging strategies and improve the overall risk-return trade off an investor faces.

A new market timing model based on ANNs is developed which forms the heart of the proposed decision support system. The system analyses stockmarket and futures data and makes a prediction about expected stock market conditions one month ahead. The proposed ANN based hedging strategy uses stock index futures to protect the portfolio against downturns in the share market.

Overall, this thesis concludes that the proposed model achieves a significant improvement in the risk-return tradeoff compared to the benchmark hedging strategies in the Australian stockmarket.

Additional Publications

The following is a list of publications by the candidate on matters relating to this thesis.

B. Krollner, B. Vanstone and G. Finnie (2010). Financial time series forecasting with machine learning techniques: A survey. Proceedings of the 18th European Symposium on Artificial Neural Networks - Computational Intelligence and Machine Learning (ESANN 2010), Bruges, Belgium.

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This thesis is dedicated to my family for always being there for me.

To my mother Karin and my father Heinz-Dieter.

To my brother Dirk and his family.

Last but not least, to my wife Ximena.

Thank you for your unconditional love and support.

Contents

List of Figures

List of Tables

1. Introduction

Stock market prediction with machine learning techniques is a popular field of research due to the potential profit making opportunities. A less frequently analysed field is the application of machine learning techniques in the domain of risk management.

The aim of this thesis is to evaluate if machine learning techniques can enhance decision-support systems in the area of financial risk management. In particular, selective stock index hedging strategies based on artificial neural network (ANN) forecasts will be analysed.

The aim of risk management and hedging in particular is to control or reduce the risk of adverse price movements. Stock index futures offer the opportunity to manage the market risk of investment portfolios. Hedging is an important tool for institutions like banks and superannuation funds to manage risks associated with stock market investments.

The motivation of this research is to examine the factors influencing the price movements in the stock index futures markets using different machine learning approaches. It investigates whether soft computing can improve existing forecasting models. A new machine learning enhanced decision-support system will be proposed that allows hedgers to increase their expected return while practising the hedge against unfavourable movements in the stock market.

The proposed research will focus on the computational aspects of modelling and parameter estimation of stock index futures hedging.

1.1. Motivation and statement of problem

Stock index forecasting is important for making informed investment decisions. Events like the global financial crisis show that investing in the stock market can potentially lead to high losses for the holder of common shares. Company specific risk can be reduced by diversification. However, systematic market risk that affects the whole stock market can have a large negative impact on portfolio returns. Derivatives based on the stock index, like stock index futures, can be used to protect a portfolio against unfavourable moves in the stock market. In this thesis, a market timing model based on artificial neural networks (ANNs) is developed. This model is used to predict the stock market one month ahead. Depending on the result of the prediction stock index futures are used to protect the portfolio against downturns in the share market.

A hedging model based on artificial neural networks is created and the model is compared to the performance of the two naive investment strategies of never hedging and always hedging, as well as the two more common strategies based on the futures premium and excessive volatility models. The objective of this study is to provide risk managers with additional information about the state of the stock market so that they can make more informed investment decisions. Risk managers need to decide when to leave a portfolio unhedged to generate profit and when to hedge in order to control downside risk. (Topaloglou et al. 2008)

Machine learning techniques are frequently used in the area of stock market prediction. Less frequently, ANNs are applied in the domain of portfolio risk management. (Krollner et al. 2010)

The contribution of this research is to fill this gap by applying the existing body of literature in stock index forecasting with machine learning techniques to the domain of portfolio risk management. This study analyses whether strategies to predict movements in the stock index can be used to derive hedging strategies and improve the overall risk-return trade off an investor faces.

1.2. Aims and research question

The issues related to risk management mentioned before lead to the following general research question:

”Can artificial neural networks be used to improve the effectiveness of dynamic hedging strategies in the Australian stockmarket?”

The literature review reveals that there are a significant number of studies trying to forecast movements in the stockmarket, but there is a lack of literature trying to improve stock market risk management strategies with machine learning techniques. This thesis addresses the research question in the context of a 10 year period of Australian stock index data starting in May 2000 and ending in April 2010.

A variation of ANNs are trained and benchmarked against other risk management strategies. A methodology for creating and benchmarking hedging strategies for portfolios of shares is developed and detailed in the methodology section. In addition, it is explained how the effectiveness of hedging strategies can be measured so that it is possible to assess the benefits of using machine learning techniques quantitatively. The methodology section provides a guide of how the research question is addressed.

As part of this thesis the following hypotheses are evaluated:

- **Hypothesis 1**
  Selective hedging strategies based on artificial neural networks that use a binary hedging method can improve the hedging effectiveness in relation to conventional hedging strategies.

  The term binary hedging means in this context that a portfolio of shares is either fully protected or fully unprotected.

- **Hypothesis 2**
  Selective hedging strategies based on artificial neural networks that use a continuous hedging method can improve the hedging effectiveness in relation to conventional hedging strategies.

  Continuous hedging means that the portfolio is always hedged, but the degree of hedging varies according to the strength of the ANN output signal.

1.3. Main contributions

There is a large body of literature in stock index forecasting with machine learning techniques and the main reasons quoted in literature to justify the research are:

1. Improvement of trading performance

2. Usefulness for portfolio hedging

However, the performance of the analysed systems is almost always evaluated in terms of trading performance. There are hardly any publications which analyse the usefulness of stock index prediction for hedging purposes.

This thesis aims to fill this gap by investigating if the decision making process in the risk management domain can be enhanced by machine learning techniques.

This is important for investors because risk management strategies like hedging can be used to protect funds against unfavourable moves in the stock market. If an investor is uncertain about the economic situation, but thinks that his portfolio has been chosen well and will outperform the market, financial derivatives like stock index futures can be used to protect the portfolio against downturns that affect the market as a whole. The hedged portfolio is then not affected by market moves and is only exposed to the performance relative to the market. A strategy of selling the whole portfolio temporarily and buying it back later might lead to significant transactions costs. Stock index futures can be used for short-term protection in an uncertain market condition. (Hull 2008)

In general, stock market participants face the problem of having to make estimates about future directions of the stock market and face the uncertainty of not knowing when and how long to hedge. This study intends to solve this problem by applying the existing body of stock index forecasting literature to the domain of dynamic portfolio hedging.

Building on the existing literature, this research intends to contribute to the current body of knowledge, as described below:

- Showing that machine learning techniques can be used to enhance the hedging effectiveness of risk management strategies.
- Development of an early stopping algorithm for neural network training based on financial metrics (e.g. Sharpe Ratio) instead of statistical metrics (e.g. MSE)
- Contribute a methodology for building and testing hedging strategies using ANNs by extending the methodology of Vanstone & Finnie (2009) to the domain of portfolio risk management

1.4. Thesis outline

The following chapter covers the literature review which analyses literature that is relevant to this study. In particular, recent developments in the areas of risk management, stock index forecasting and soft computing are evaluated and gaps in the literature are revealed. The literature review concludes with the statement of the research question which addresses the gaps found in the literature. The literature review also forms the base for design decisions which need to be made in the process of creating the proposed decision support system.

The third chapter introduces the methodology employed in this study. In particular, the process of creating and benchmarking machine learning enhanced risk management strategies is described. In addition, related issues regarding data adjustment, variable selection, and the software used are presented. Again, each choice made in the methodology is supported by the relevant literature. At the end of the methodology chapter, the research question is presented and it is explained how the research question can be answered in the context of the methodology framework.

The fourth chapter shows the results of this study. The methodology is applied by creating the proposed decision support system and performing a trading simulation on out-of-sample data. An analysis of data is performed and the results are presented. The key metrics discussed in the methodology chapter are calculated and a comparison to alternative risk management strategies is made.

The last chapter concludes this study by reflecting on the results found in the previous chapter. The research question is restated and an answer to the research question is given in the context of the simulation results. In addition, future possible research directions are identified and discussed.

2. Literature Review

This chapter analyses literature that is relevant to risk management and stock market forecasting with a focus on machine learning techniques.

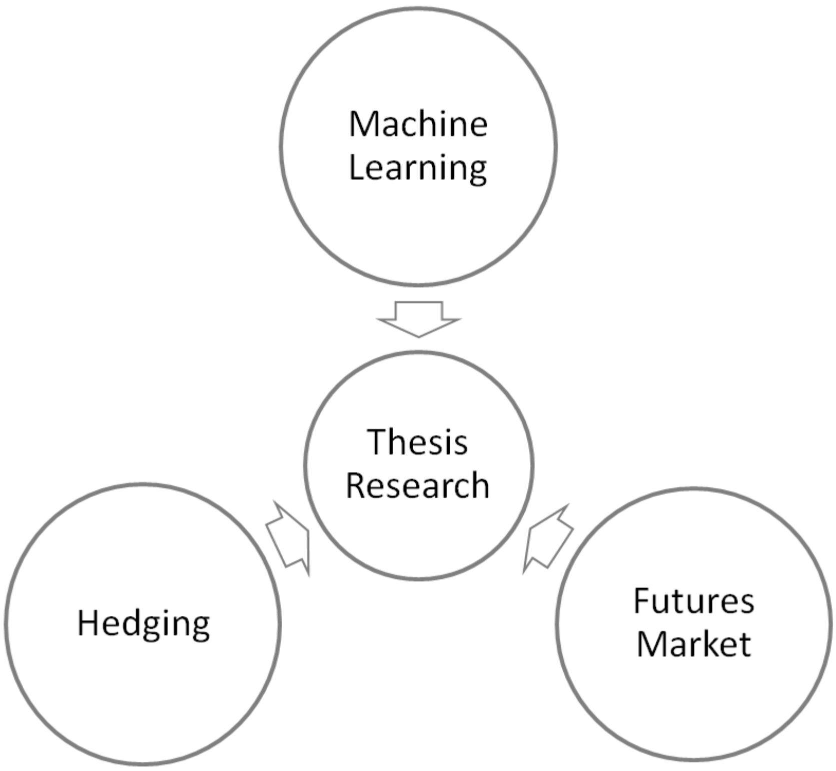

Figure 2.1.: Central research theory and related areas

Risk management is an important research area since it can potentially be used to avoid the financial distress resulting from events like the global financial crisis. There is a large body of literature in the areas of risk management and stock market prediction.

Changes in the stock market are non-linear and are influenced by many internal and external factors so that stock market forecasting poses a great challenge for researchers. (Shen et al. 2011)

Figure 2.1 shows the focal theory of this thesis as a combination of three research areas.

The following sections will introduce the related research areas and present current developments. Gaps in the literature will be presented which form the basis of this thesis. In particular, the following areas will be discussed:

- **Futures Market**
  This section will give an overview of the types of traders participating in the futures market and the process of price discovery. Recent developments in the literature of futures price forecasting are presented. A particular emphasis will be on the literature of predicting stock index futures prices.

- **Hedging**
  The section about hedging will review risk management strategies across various markets. The purpose of hedging will be discussed and dynamic hedging strategies will be presented. Also, literature in hedge ratio estimation, a key component of hedging strategies, will be analysed.

- **Machine Learning**
  The machine learning section will put a particular emphasis on machine learning techniques that are applied in the area of stock index forecasting. The literature review includes variable and parameter selection issues and recent developments in the area of machine learning based stock market forecasting.

2.1. The futures market

Futures contracts and in particular stock index futures play an essential part in the decision support system proposed in this thesis. This section will give an overview of the current literature in the area of futures trading and futures price discovery.

Hull (2008) defines futures and forward contracts as an agreement to buy or sell an asset at a future time for a certain price. Futures are standardised contracts which are traded at exchanges. In contrast, forward contracts are traded *over-the-counter*, which means that these contracts are private agreements between financial institutions.

A large portion of traded futures contracts do not lead to the delivery of the underlying asset. The contracts are closed out before the delivery period is reached. The price of futures contracts and underlying spot prices might diverge in short time frames. However, the possibility that delivery could be taken leads to the effect that futures and spot prices converge at the end of the contract period.

According to Figuerola-Ferretti & Gonzalo (2010) futures markets have two main purposes:

1. Futures markets facilitate price discovery.

2. Futures markets offer a means of transferring risk or hedging.

2.1.1. Types of traders

In the futures market, three main types of traders exist: hedgers, speculators and arbitrageurs. Hedgers are usually in a position in which they want to buy or sell an asset at a future point in time and face a risk associated with the varying future price of the asset. Therefore, hedgers can reduce the price risk by purchasing futures contracts that offset the losses associated with adverse price movements. In contrast, speculators are betting on future price moves of an asset in order to make a profit. The third group of traders are arbitrageurs. They try to identify price discrepancies in different markets for the same asset. They can lock in a profit by buying the asset in one market and selling it in another market at a higher price at the same time. Arbitrageurs usually buy and sell large amounts of an asset, so that the prices are forced to an equilibrium. Therefore, arbitrage opportunities only exist for a very short time. (Hull 2008)

Tornell & Yuan (2009) investigate the relationship between speculators and hedgers in the currency futures markets in order to investigate if futures trading activities convey information upon futures price movements. The authors transform trader positions into economic measures to analyse if there is an information content. The study finds that if the market is dominated by speculative activity, there is a tendency of the price trends to continue. In contrast, if the market is dominated by hedgers, a price reversal is more likely to happen. The authors conclude that the data about net positions of different types of traders contain valuable information which can be translated into profitable trading strategies.

2.1.2. Determination of futures prices

According to Hull (2008), the factors of the price of a futures contract depend on whether the underlying asset is primarily held for investment or for consumption purposes by the investor.

2.1.2.1. Investment Assets

Investment assets, like stocks, gold or silver, are assets which are held by the majority of investors for investment purposes. For a simple non dividend paying asset the price of the futures contract can be calculated as shown in equation 2.1.

$$F_0 = S_0 e^{rT} \tag{2.1}$$

F_0 is the current price of the futures contract, S_0 is the current spot price of the asset underlying the futures contract, r is the interest rate per annum expressed with continuous compounding, and T represents the time until the delivery date (in years).

2.1.2.2. Consumption Assets

Assets which are used primarily for consumption rather than for investment purposes usually provide no income, but are subject to significant storage costs. For consumption assets equation 2.1 needs to be extended for the storage costs u, expressed as a constant proportion of the spot price.

$$F_0 = S_0 e^{(r+u)T} \tag{2.2}$$

2.1.2.3. Convenience Yields

For consumption commodities equation 2.2 is not always valid. There are situations when users of a commodity feel that the ownership of the commodity provides advantages compared to the ownership of a futures contract. For example, an oil refining company benefits from owning the actual crude oil so that the refining process can keep running. A futures contract in crude oil does not provide the same advantage to the company. In general, manufacturers profit from owning a physical asset because they can keep operating and benefit from temporary local shortages. These benefits from holding the physical assets are called convenience yield. The calculation of the futures price F_0 including the convenience yield y is shown in equation 2.3.

$$F_0 = S_0 e^{(r+u-y)T} \tag{2.3}$$

2.1.2.4. Cost of carry

According to Hull (2008), the relationship between futures prices and spot prices can be summarised as the cost of carry. The cost of carry includes the storage costs plus the interest that is paid to finance the asset less the income earned on the asset. Equation 2.4 shows futures price F_0 for an investment asset including the cost of carry c.

$$F_0 = S_0 e^{cT} \tag{2.4}$$

For consumption assets the futures price is

$$F_0 = S_0 e^{(c-y)T} \tag{2.5}$$

where y is the convenience yield.

2.1.2.5. Stock Index Forecasting

According to Frino (2005), a stock index measures changes in a portfolio of shares and is often used to benchmark fund managers to assess the performance in comparison to the market. In Australia, the All Ordinaries Index was the main index from 1979 to 2000. The index was composed of the top 300 companies listed on the Australian Stock Exchange (ASX). The All Ordinaries Index was calculated by the ASX. In 2000, the ASX introduced a new family of stock indices with the S&P/ASX 200 being the most commonly used as a benchmark. The S&P/ASX 200 is roughly based on the 200 listed companies which have the largest market capitalisation and are most actively traded. The

All Ordinaries Index still exists but is considered to be too big and cumbersome since it consists of 500 companies today.

The S&P/ASX 200 is calculated by Standard & Poor's (S&P) which is a division of McGraw-Hill. According to Frino (2005) the following updating formula is used for calculation purposes:

$$I_t = I_{t-1} * \frac{marketvalue_t}{marketvalue_{t-1}} \tag{2.6}$$

I_t is the index at time t and the $marketvalue_t$ is calculated by multiplying the share price with the number of securities on issue of all securities in the index. For calculation purposes the index is assigned a starting base value of 500 at 31 December 1979.

2.1.2.6. Cost of carry for stock index futures

An important property of the S&P/ASX 200 index is that changes in the index are purely driven by changes in the share price of the underlying companies. With the exception of accumulation indices, dividends are not considered so that it does not reflect the true return from buying and selling the securities in the index. However, dividends need to be taken into account when calculating the fair value of stock index futures. According to Frino (2005), the fair value of stock index futures is calculated as shown in equation 2.7.

$$F_0 = S_0 * (1 + r_t) - d_t \tag{2.7}$$

The value of the stock index S_0 is multiplied with the risk free rate r_t since the funds can be invested in risk free instruments like bonds until the contract matures. However, the dividends paid between the futures trade date and the settlement date d_t need to be subtracted from the price of the stock index futures contract.

2.1.2.7. Risk and Return

According to the seminal works of Keynes (1930) and Hicks (1939), a major factor in pricing futures contracts is the level of risk involved in holding the contract. For example, if hedgers tend to hold short positions while speculators tend to hold long positions, the futures price will be lower than the expected future spot price. Speculators require compensation for the risks they are bearing and will trade only if they expect to make money on average. In contrast, hedgers will lose money on average. However, hedgers are prepared to take these losses because futures contracts reduce their risks. If hedgers tend to hold long positions and speculators tend to hold short positions, Keynes and Hicks state that the futures price will be higher than the spot price for the same reason.

Benth et al. (2008) state that the market risk premium is defined as the difference between the futures and spot prices. The risk premium depends on the risk aversion of market participants and the interaction between buyers and sellers. The authors state that the risk premium is an indication of the behaviour of traders and their view of the market in short and long term horizons. The main contribution of Benth et al. (2008) is that they provide a framework which links the market risk premium, the market price of risk, and the market players' risk preferences.

2.1.3. Technical Analysis

Technical analysis is a price forecasting technique based on past prices, volume and open interest. Pring (2002) describes the following justification for the use of technical analysis:

> ”The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend

> reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed." (Pring 2002, p.2)

According to Yen & Hsu (2010), technical analysis is a popular trading strategy in the futures markets. Participants in the futures markets tend to rely on technical analysis rather than fundamental analysis. The authors state that in particular, measures like price movements and changes in trading volume play an important role when analysing futures prices.

Shen, Szakmary & Sharma (2007) analyse momentum strategies in commodity futures markets. Three main differences between the stock and futures market are pointed out:

1. The transaction costs in the futures market are lower, so that momentum strategies can be implemented at lower cost.

2. In the futures market, taking a short position is as easy as taking a long position.

3. Commodity prices are not driven by analyst recommendations or corporate announcements. The commodity markets and equity market exhibit very different time series properties.

The authors conclude that momentum strategies can generate significant profits in the futures market in short and medium time horizons.

Pukthuanthong et al. (2006) suggest that simple trend following systems do not work in the major currency markets any more. Instead, they discovered that trend following still works in exotic currency markets. However, even these exotic markets have become more efficient in recent years.

In contrast, Koh & Lee (2007) describe a short term trading strategy based on historical volatility (HV) and implied volatility (IV). When the 90-minute moving average (MA) of the HV crosses the 180-minute MA a trading signal is generated. The trading direction is indicated by the implied volatility. When the 75-minute IV is greater than the 165-minute

IV a long position should be entered. A short position should be established otherwise. An exit signal is given when the 75-minute IV crosses the 165-minute IV. The authors report a 56% profit trading the KOSPI 200 index futures contract at the Korea Exchange from November 2005 to December 2006.

Salm & Schuppli (2010) analyse the behaviour of investors in the stock index futures markets and find strong evidence of trend-chasing behaviour across the majority of the 32 examined markets. In particular, the authors state that a lot of traders seem to chase short-term to medium-term trends. The strongest indication of this trading behaviour can be found during market downturns.

Hsu et al. (2009) examine strategies of improving the overall profit and lowering the psychological pressure for investors in the Taiwan futures markets. The psychological pressure is measured in terms of the number of times a strategy is profitable and the maximum equity drawdown. The authors use the following list of technical indicators in their study: moving average, phase change index, relative strength index, psychological line, contrary Williams index, linear regression reversal, Chande momentum oscillator, and the Fisher's index for relative strength (MAWRSI-Fisher). The authors conclude that they were able to improve profits and reduce psychological burden on investors efficiently.

According to the practitioners magazine *Technical Analysis of Stocks & Commodities* (2007) the most popular technical variables in the futures market used by practitioners are the following indicators: Moving Average Convergence/Divergence (MACD), Relative Strength Index (RSI), Stochastics and Bollinger Bands.

Menkhoff & Taylor (2007) argue that technical analysis is an important tool in the foreign exchange market. Four arguments to explain the profitability of technical analysis strategies are analysed:

1. The market may not be fully rational.

2. Technical analysis may exploit the influence of official interventions.

3. Technical analysis may be an efficient form of information processing.

4. Technical analysis may inform on non-fundamental influences.

Menkhoff & Taylor (2007) conclude that, while all four arguments may have some validity, argument number four is the most plausible. Technical analysis is used as a tool to inform about non-fundamental influences like market sentiment and psychological influences on price. The fact that technical analysis is frequently used by practitioners makes it an intrinsic part of the market. Therefore, the authors argue that researchers must understand and integrate technical analysis into economic reasoning.

2.1.4. Random Walk Trading

The term 'Random Walk' was used in the seminal work of Fama (1965) and became popular after the publication of the book 'A Random Walk Down Wall Street' by Malkiel (1973).

The random walk hypothesis states that stock market prices evolve according to a random walk and thus the prices of the stock market cannot be predicted. Naive prediction models based on the random walk hypothesis use the current period's price as the best estimation for the next period's price.

In the futures market the situation is slightly more complex. The futures price of the next period could be this period's futures price or this period's spot price. Thomas (1986) argues that if spot prices follow a random walk, the current spot price is the best predictor for the next period's spot price. Further, Thomas (1986) states that if the futures price of a commodity represents the expected future spot price, then the spot and futures price should be equal. If these prices differ, either futures prices contain a risk premium or futures traders believe that they can make a better prediction of the futures price compared to the random walk model.

Atkins & Basu (2004) create a trading strategy based on the random walk model for foreign exchange futures. The strategy simply buys futures contracts that are below the current spot price and short sell futures contracts that are above the current spot price. During the analysed period from January 1990 to March 2003 the described strategy leads to 63.2% of the trades in a profit. The author performs various simulations and reports annualised returns between 5.18% and 14.76%.

Pukthuanthong et al. (2007) also test the theory of currency futures following the random walk hypothesis. A simple strategy is developed, which utilises the difference between spot price and futures price of a currency. The model suggests to buy currencies which trade at a discount and sell currencies that trade at a premium. In their simulation, the authors achieve a significant profit.

Rast (2001) tries to predict price movement in crude oil. The main contribution of the article is that the author shows that prediction accuracy is improved when two separate forecasting models are used for the two market states contango (futures price is higher than spot price) and backwardation (futures price is lower than spot price).

Overall, the random walk model is frequently used in the literature as a benchmark for evaluating futures trading and hedging strategies.

2.1.5. Time Series Analysis

2.1.5.1. Regression

Early work of using regression analysis in the futures market includes Schwager (1984), who later published a series of bestselling books called ”Schwager on Futures”. In his books, Schwager builds forecasting models using multiple regression and intermarket analysis. When creating a model, Schwager firstly identifies variables that are correlated to the prediction output and then performs a stepwise regression analysis. For example, Schwager describes 17 indicators that have an influence on the movements in the

S&P 500 futures prices. According to Schwager, each of these indicators must pass the following criteria in order to be useful in a forecasting model:

- **Logical Explanation for Relevance**
  There must be a rational reason why an indicator has a significant effect on the stock market.

- **Large Impact**
  There should be a strong correlation between the indicator and the forecasted variable.

- **Longevity of Influence**
  The indicator should have affected the market over extend periods of time and under varying market conditions.

- **Suited to Objective Evaluation**
  The indicator must have timely reporting of data and should not be subject to subsequent major revisions.

The 17 indicators are based on information of the earnings growth, monetary policy, interest rates, state of the economy, business cycle, inflation information and market sentiment. Schwager uses a position weight between -100 and 100 percent which represents a futures trader's perspective (an investor's perspective would be between 0 and 100 percent). Schwager argues that adjusting the position size according to the strength of the forecasting signal leads to higher return/risk characteristics. A binary approach, e.g. going 100 percent short or going 100 percent long depending on a signal threshold, leads to a higher absolute return since the average position size is much higher, but is not superior in regards to the return/risk trade-off.

More recently, Tse & Chan (2010) analyse the lead-lag relationship between the futures and spot markets of the S&P500 using the threshold regression model. The authors find that the lead effect of the spot market is stronger in periods of directionless trading than in periods of strong trending markets.

2.1.5.2. ARIMA/GARCH

The autoregressive integrated moving average (ARIMA) method is a forecasting technique which is often used as a benchmark for neural networks with purely technical inputs. (Ntungo & Boyd 1998) (Dunis & Nathani 2007)

The ARIMA model consists of an autoregressive (AR), integrated (I) and moving average (MA) part.

A model used for volatility forecasting is the General AutoRegressive Conditional Heteroskedasticity (GARCH) model where the variance rate follows a mean-reverting process. These models are usually employed in modelling financial time series that exhibit time-varying volatility clustering. (Hull 2008)

Fatima & Hussain (2008) develop a model for the prediction of Karachi Stock Exchange index (KSE100) data. The authors use a combination of ANNs and ARIMA, as well as ARCH/GARCH models. The hybrid systems are compared to pure ARIMA and ARCH/GARCH models. The study concludes that the hybrid ANN model using ARCH/-GARCH data is superior to the other analysed models in predicting the KSE100 index.

Mohammadi & Su (2010) evaluate the usefulness of several ARIMA-GARCH models in eleven international crude oil markets. While the authors report mixed forecasting results, the APARCH models outperfoms the other examined models.

Hossaina & Nasser (2011) compare a mixtures of ARMA-GARCH models to standard back propagation ANNs and support vector machines to predict changes in the Nikkei 225 and S&P 500 stock indices. The authors find that the support vector machines show the best performance in regards to the forecasting error, while the ARMA-GARCH model performs best in terms of predicting the correct direction of changes. Hossaina & Nasser (2011) conclude that support vector models are quite simple and have better interpretability properties compared to complex GARCH type and ANN models and that support vector machines can still be used successfully in forecasting financial returns.

2.1.6. Time to expiration and futures price volatility

In his seminal paper, Samuelson (1965) states that the volatility of futures prices should increase when the contract approaches expiration.

> "High price volatility implies big price changes. Price changes are large when more information is being revealed about a commodity. Early in a futures contract's life, little information is known about the future spot price for the underlying commodity. Later, as the contract nears maturity, the rate of information acquisition increases. For example, little is known about a corn harvest a full year before harvest time. As the harvest approaches, the market gets a much better idea of the ultimate price that corn will command. For a futures contract expiring near the harvest, Samuelson's model implies that the futures price should be more volatile as the harvest approaches, and most studies support the hypothesis." (Hull 2008, p.110)

Sanders et al. (2007) analyse the information content in deferred futures prices for the live cattle and hog markets. The authors examine the informational role of contracts from the two- to twelve month horizons. The results indicate that there is unique information in the cattle futures prices up to the ten-month horizon while hog futures prices contain additional information in all analysed periods.

According to Frino & McKenzie (2002) there is a large body of literature in the area of pricing efficiency of stock index futures markets. "The bulk of this literature has considered the pricing efficiency of futures contracts relative to the cash market. [...] A second and less frequented area of this literature has considered the relative pricing efficiency of stock index futures contracts of different maturities (i.e., intramarket or calendar spreads)." (Frino & McKenzie 2002, p.452)

2.1.7. Australian SPI 200

The SPI 200 futures contract is the benchmark contract in Australia, based on the S&P/ASX 200 stock index, and amongst the 12 most actively traded stock index futures contracts in the world (Frino 2005). In contrast to the ASX/S&P 200 stock index, there is no continuous time series for SPI 200 futures contracts. Australian futures markets are comprised of individual contracts which expire four times a year in March, June, September and December. As contracts expire, new contracts are listed up to 18 month ahead.

The ability to short sell SPI 200 futures contracts as well as the strong correlation to the ASX/S&P 200 index makes the SPI 200 futures a valuable tool for portfolio risk management in the Australian stock market.

Futures prices have some unique characteristics. In contrast to stock data, futures data does not consist of a single continuous time series. Figure 2.2 shows that there are several futures contracts trading at the same time for the ASX stock index. The difference between these contracts lies only in their expiry date.

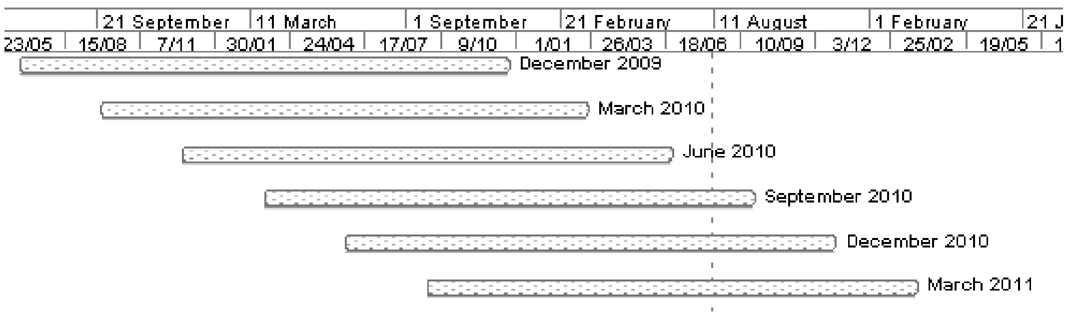

Figure 2.2.: ASX SPI 200 Index Futures

Although the stock index futures contracts start trading up to 18 month ahead, most of the trading activity takes place in the three to four month before contract expiry. For example, figure 2.3 shows the June 2010 ASX SPI 200 futures contract. The volume shown in the lower half of figure 2.3 is much higher between March 2010 and June 2010 in comparison to the preceding period.

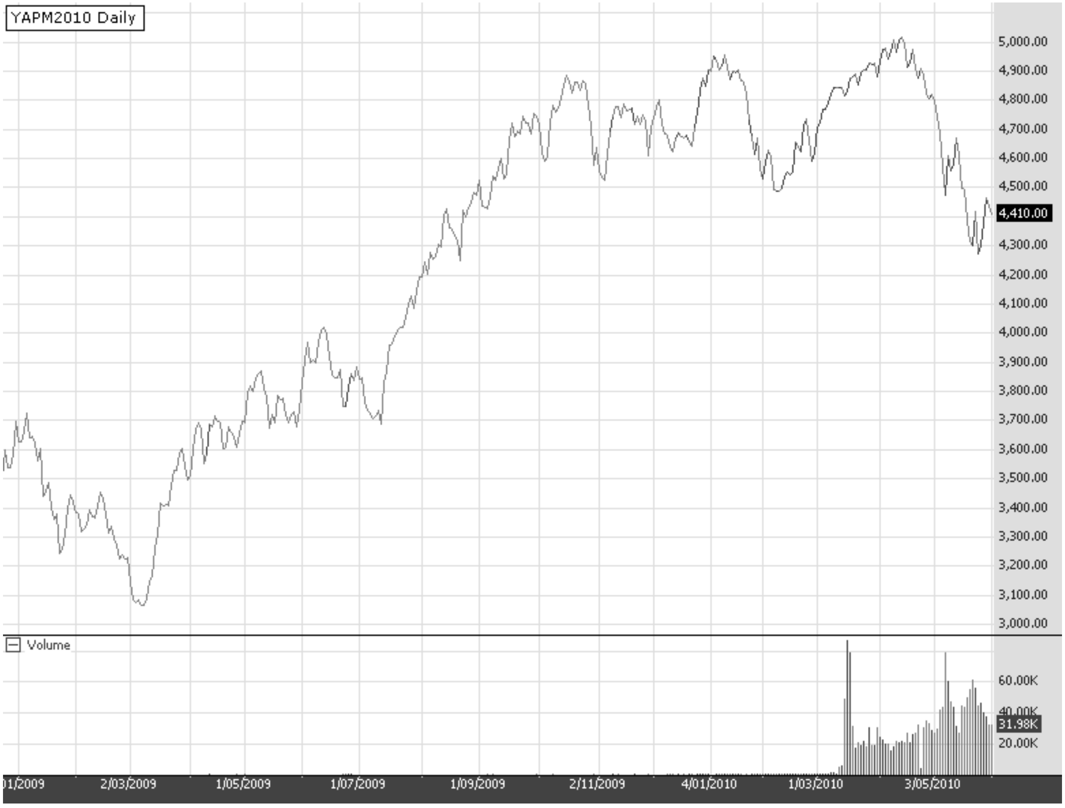

Figure 2.3.: June 2010 ASX SPI 200 Futures Contract (YAP)

Futures contracts have a limited lifespan and therefore exhibit different characteristics compared to continuous time series data like stock data. The literature review revealed that there is a lack of machine learning literature which takes these specific characteristics of futures contracts into account.

2.2. Hedging

The stock index futures described in the previous section can be used for risk management and in particular for hedging purposes. The decision support systems proposed in this thesis aim to improve the risk-return tradeoff an investor faces. The following sections will introduce the concept of hedging and elaborate on different views on the purpose of hedging found in the literature. A particular focus is put on current literature in the area of hedging with stock index futures.

2.2.1. Hedging Principles

Hedging is a risk management strategy to reduce a particular risk. Hedgers are usually in the possession of an asset and use an opposite offsetting position to manage that risk. For example, futures contracts can be used as offsetting positions for investments in oil, currencies, and the stock market.

The goal of hedging is to minimize the exposure to unwanted risk. In the stock market, investors are concerned with risks like company specific risk and systemic risk that affects the whole stock market. Company specific risk can be addressed through diversifying investments e.g. over a large number of companies. One way of handling systemic risk is the use of stock index futures.

For example, a fund manager that owns a portfolio of shares, and believes that a downward movement in the market will occur, can short sell stock index futures. In the case of an adverse movement, a profit in the futures market is generated so that the loss on the portfolio of shares is offset by a gain in the futures market. In theory, when the portfolio and futures are perfectly correlated and the transaction is properly constructed the loss on the portfolio will be exactly offset by the gain in the futures market. However, in the case that the prediction of the investor proves to be incorrect, gains on the portfolio of shares are also offset by losses in the futures market. (Frino 2005)

2.2.2. Objective of Hedging

Floros & Vougas (2004) state that ”[t]he main objective of hedging (i.e. risk management) is controversial, and there is no clear view on the purpose of hedging. Nevertheless hedging is the most important function of futures markets (that is trading in index futures), the origin of the term is unclear. Hedging uses futures markets to reduce risk of a cash market position. In general, hedge is the action taken by a buyer or seller to protect his/her business or assets against a change in prices. It is the act of reducing uncertainty in value fluctuations of financial portfolios by combining a portfolio of risky assets with a position in a financial instrument, which is highly negatively correlated with the portfolio. Thus, the objective is that positive (negative) in value fluctuations of the portfolio will be off-set by negative (positive) in value fluctuations of the hedging instrument.”

The traditional view in the literature describes risk reduction as the main purpose of hedging. Hedgers are seen as risk adverse and are concerned with the minimization of the risk associated with holding an asset. Risk reduction is achieved by holding an asset and futures contracts that offset price fluctuations in the asset. Ideally, movements in the asset and futures contracts are of equal magnitude, but opposite direction.

The seminal work of Johnson (1960) and Ederington (1979) describe the objective of hedging as to minimize the variance of the portfolio of asset and futures positions. The overall goal is to compose a portfolio with reduced risk.

An alternative thread of literature is based on the early work of Working (1953) which uses hedging for the purpose of profit maximisation. A profit is achieved by speculating on the difference between the asset and the futures position.

Howard & D’Antonio (1984) state that hedging is primarily used to enhance the risk-return trade-off. Ghosh (1993, p.743) argues that the goal of ”hedging is to minimise the risk of the portfolio for a given level of return.”

Floros & Vougas (2004) summarise that hedging can reduce risk and improve planning flexibility. The authors state that hedging is carried out for a number of different reasons and list the following main objectives of hedging found in the literature:

- Eliminate risk due to adverse price fluctuation.
- Reduce risk due to adverse price moves.
- Profit from changes in the basis.
- Maximize expected return for a given risk and minimize risk for a stated return.

2.2.3. Cross Hedging

The SPI 200 is based on the S&P/ASX 200 index. In terms of stock portfolios, cross hedging occurs when the portfolio differs in composition from the constituents in the S&P/ASX 200 index. For example, a portfolio manager might have a high exposure to companies in the energy sector. Because there is no futures contract on the energy sector in the Australian stock market, the portfolio manager might choose to use the SPI 200 contract to hedge the exposure.

In a cross hedging scenario, the price movements in the futures contract and underlying asset are not perfectly correlated so that the hedge ratio needs to be calculated.

”The hedge ratio is the ratio of the size of the position taken in futures contracts to the size of the exposure. When the asset underlying the futures contract is the same as the asset being hedged, it is natural to use a hedge ratio of 1.0. [...] When cross hedging is used, setting the hedge ratio equal to 1.0 is not always optimal. The hedger should choose a value for the hedge ratio that minimizes the variance of the value of the hedged position. ” (Hull 2008, p.54-55)

The minimum variance hedge ratio is calculated by performing a regression between the returns of the stock portfolio and the returns of the futures contracts. The hedge ratio is equivalent to the regression slope. Although there are a variety of ways to estimate hedge ratios, Floros & Vougas (2004) state that hedge fund managers commonly use the ordinary least squares (OLS) regression to calculate futures hedge ratios. The hedge ratio is periodically recalculated as the correlation between portfolio and futures contract might change over time.

2.2.4. Reasons for Hedging an Equity Portfolio

In theory, when a portfolio of stocks is perfectly hedged, the portfolio grows at the risk free interest rate. Therefore, the question naturally arises why the investor should go through the trouble of using stock index futures contracts to earn the risk free rate. The investor could simply sell the portfolio and invest in risk-free instruments like Treasury-bills. One reason for using stock index futures is that the investor feels that the portfolio of the stocks has been chosen well and is confident that the portfolio will outperform the market. If the investor is uncertain about the economic situation, stock index futures can be used to protect the portfolio against downturns that affect the market as a whole. The hedged portfolio is then not affected by market moves and is only exposed to the performance relative to the market. A second justification for using stock index futures is that the hedger plans to hold the portfolio for a long time. Selling the portfolio temporarily and buying it back later might lead to significant transaction costs. In this case, stock index futures are used for short-term protection in an uncertain market condition. (Hull 2008)

2.2.5. Dynamic Hedging

Stulz (1996) states that there is a apparent conflict between the theory and practice of risk management. The author states that companies often use risk management strategies for other goals than reducing variance. Stulz (1996) describes a practice of dynamic hedging which he calls 'selective' as opposed to 'full-cover' hedging. It is argued that corporate users do not use derivatives for pure speculation, but there seems to be a tendency that the choice of hedge ratio is influenced by the view of future interest rates, exchange rates, and commodity prices. The goal of such a strategy is to reduce downside risk while preserving as much upside potential as possible.

Yun (2006) provides an excellent introduction into dynamic hedging. The following quote from Yun (2006, p.3496) is presented in the following paragraph because dynamic (selective) hedging is a central part of this thesis.

> "[Selective hedging] refers to a hedging strategy based on the hedger's market expectations by which he may chose to hedge only part of his position or not at all. Contrary to this concept, the term 'blind hedging' or routine hedging corresponds to the practice of not deviating from a fully planned hedging strategy, with volumes, contracts, and entry and exit points established prior to the execution of the hedge (NYMEX, 2004). In a selective hedging, the execution of the overall strategy can be fine-tuned to better reflect ongoing cash market conditions. Thus, if continuously increasing prices were assumed, it is unlikely that a producer would blindly stick to his losing short hedges, rather than liquidate early to contain his future losses. A selective hedging, for example, might link the volume to be hedged to an ongoing assessment of the cash-futures or cash-forward basis relationship and the perceived likelihood of a reduction in posted prices.
>
> A trader decides whether to hedge or not according to price expectations. For instance, a future cash buyer would take a long position in futures or forward with certain maturity when a forecasted spot price prevailing at maturity exceeds the current futures or forward price with the given maturity. Contrary to this, his cash position is left unhedged when the forecasted spot price is below the current futures or forward price. Alternatively, a commodity holder hedges if price are expected to fall, and does not hedge if prices are expected to rise.

> Selective hedging by companies appears to be widespread. This common hedging procedure is often done to prevent large losses, and it can relate to optimal hedging rather than simply minimizing risk. Obviously, it is assumed that the trader must have skills in anticipating future price movements."

McCarthy (2003) argues that a passive hedger has the options to hedge every exposure with a futures contract or to remain unhedged. In contrast, a selective hedger makes a judgement on each exposure. When it is believed that the market will move in a favourable direction, the exposure would remain unhedged. If on the other hand the market in expected to move in an unfavourable direction, the exposure should be hedged.

Selective hedging strategies are frequently employed in areas where hedgers are big companies with superior knowledge about supply and demand and in the domain of hedging currency risks in international portfolio investments.

Knill et al. (2006) state that historical evidence indicates that most firms in the oil and gas industry employ a selective hedging strategy. The companies establish hedge positions only if they expect imminent unfavourable conditions.

Adam et al. (2008) examine why firms hedge selectively and find that small firms speculate more than large firms. The authors point out that one reason why firms hedge selectively may be that managers erroneously believe that they can outperform the market.

Topaloglou et al. (2008) use a dynamic stochastic programming model to manage risk in assets price and exchange rates in a international portfolio context. The study finds that selective hedging strategies are effective in controlling risk and generating a stable return path.

Kim et al. (2001) investigate local polynomial kernel forecasts for the management of price risks in hog and corn futures markets. The study indicates that combining hedging with forecasts can potentially enhance price risk management.

McCarthy (2003) compares strategies for managing foreign exchange exposures and finds that a selective hedging strategy based on the random walk model performs well in the analysed markets. Eun & Resnick (1997) also state that the Random Walk model is a good estimate of foreign exchange rates when analysing international equity investments with selective hedging strategies.

Simpson (2004) analyses the performance of five selective hedging strategies with foreign exchange future contracts. The author states that a strategy based on large deviations of prices compared to the purchasing power parity performs best in the examined market.

Simpson & Dania (2006) examine conditional hedging strategies for Euro currency exposures. It is found that selective hedging strategies can outperform strategies that always hedge and never hedge. Using such a strategy leads to a better risk-return tradeoff for investors.

2.2.6. Hedging with Stock Index Futures

Stock index futures are very useful for the management of stock portfolios since they directly represent the market portfolio. An important feature for portfolio management stems from the fact that stock index futures have very low transaction costs. (Kolb 2003)

Junkus & Lee (1985, p.201) state that ”large equity dealers can use the contracts to hedge against unexpected declines in their stock inventories, while the managers of large portfolios (pension funds, trust departments, insurance companies, institutional endowments, investment companies) can use futures transactions to implement market-timing decisions quickly and at relatively low cost. Individual investors can also use the index to speculate on broad market movements, or to protect their own particular portfolio in a declining market through the sale of index futures contracts.

The primary purpose of futures markets, however, has been to facilitate hedging, and stock index futures present an opportunity to apply traditional hedging theory formulated for commodities contracts in the context of capital market theory. In particular, the stock index contract allows individual investors to manage the systematic risk of their portfolio holdings though an opposing position in a futures contract; in short, the index contract may be thought of as a negative beta asset available to add to a portfolio depending on changing investor expectations and preferences."

2.3. Machine Learning

Machine learning techniques aim to automatically learn and recognise patterns in large amounts of data. In this section, an overview of the key literature in the area of machine learning techniques and artificial intelligence used for stock index prediction is given. In particular, the research motivation, the machine learning technique used, the analysed market, the input variables used, and the evaluation techniques employed are evaluated.

2.3.1. Motivation

This section reviews the motivation given by researchers for using machine learning techniques in the field of financial forecasting.

Majhi et al. (2009) identify stock market prediction as one of the most popular fields of research due to its commercial applications and the attractive benefits it offers. The large amounts of money invested in the stock market lead to investors being nervous and anxious of the future trends of stock prices in the markets.

Leung et al. (2000) state two major reasons for the success of index derivatives. Stock index trading vehicles provide an effective means for investors to hedge against potential market downturns and they create new profit making opportunities. Being able to accurately predict stock market indices has important implications and significance to researchers and practitioners alike.

Hanias et al. (2007) describe uncertainty as undesirable, but also unavoidable for an investor. The only choice an investor has is to try to reduce the uncertainty and stock exchange prediction is one means in the process.

Chun & Kim (2004) refer to the ever growing amounts of data available to decision makers. The authors state that there is the need to develop intelligent systems to generate new knowledge in order to support the decision-making process in the ubiquitous task of forecasting.

Chang et al. (2009) develop a forecasting model for the Hong Kong based Heng Seng stock market index and state that large profits can be made when a forecasting model is correct. The authors mention that large price fluctuations constitute the biggest challenge in creating an accurate forecasting model. It is argued that building a highly accurate forecasting model is a major concern for investors.

Shen et al. (2011) state that stock index forecasting is important for participants in the financial markets. The authors argue that it can be used to guard against financial risk and to monitor market fluctuations. In addition, stock index forecasting plays an important role as reference for financial research in fields like portfolio selection and the pricing of financial derivatives.

Krollner et al. (2010) divide the justifications for machine learning based stock index forecasting given in the literature into the following categories:

- **Improvement of prediction accuracy**
  It is acknowledged by a number of authors that stock index prediction is an important topic in financial forecasting and the aim of the research is to increase the prediction accuracy.

- **Decision support for investors**
  It is stated that machine learning techniques are suitable for processing large amounts of data which can give investors an improved view of the market and lead to more informed investment decisions.

- **Feasibility of stock index forecasting**
  The research motivation is to test if it is feasible to use specific machine learning techniques in the process of stock index forecasting.

- **Economic rationale**
  The rationale given is based on an economic justification like hedging against potential risks and profit making opportunities.

There is a consensus among the reviewed papers that stock index forecasting is an important field of research. However, the degree of providing a rationale for their specific research varies significantly. It ranges from only stating that stock index forecasting is important to being very elaborate about the reasons why the research is conducted. The majority of research papers state that stock index prediction plays an essential role in the financial decision making process.

2.3.2. Artificial Neural Networks

The popularity of ANN based forecasting has been growing steadily over the last years.

Hamid & Iqbal (2004) use neural networks for forecasting volatility of S&P 500 Index futures. The authors utilise closing settlement prices of 16 nearest futures contracts and 3 spot indices. The futures contracts consist of seven commodities, three Treasury obligations, and six foreign currencies. The three spot indices are DJIA, NYSE Composite Index, and S&P 500 Index. In addition, 1-day lagged S&P 500 futures prices are used as input variable. Later, 13 of the 20 variables are selected based on their correlation with the S&P 500 index. The authors conclude that the volatility forecast from the neural network provided superior results compared to implied volatilities.

Pan et al. (2005) state that a lot of AI literature focuses on emulating the human brain. However, empirical evidence shows that a lot of human traders cannot win constantly in the financial markets. Therefore, the authors describe the development of an AI system not simply as reengineering of human knowledge, but as an iterative process of knowledge discovery. In their study, the authors try to predict the direction of the Australian stock market index (AORD). Following US indices are used as input variables since the Australian stock market shows a strong correlation with these indices: US S&P 500 Index, US Dow Jones Industrial average Index, US NASDAQ 100 Index, Gold & Silver Mining Index, AMEX Oil Index. Furthermore, lagged data from the AORD is used. The authors discovered a 6-day cycle in the Australian stock market. The developed neural network reached up to 80% directional prediction correctness. However, the 80% prediction correctness cannot be used for stock index futures trading since the information of the US indices is already reflected in the futures prices during the night trading session.

Fok et al. (2008) use neural networks to predict four stock indices in the United States, Europe, China and Hong Kong. The predictions from the neural network are compared to predications made by a linear regression analysis. The authors find that the neural network predictions are more accurate in terms of the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) performance metrics.

Kumar & Haynes (2003) use an ANN to forecast credit ratings in India and find that the ANN model provides an increased speed and efficiency of the rating process. The authors state that the ANN exhibits an superior performance compared to the benchmark models.

Huang et al. (2006) propose a computational method for the selection of inputs for stock market forecasting with neural networks. The authors state that input variables should have a strong correlation to the output variable but a weak correlation to each other. If the input variables are strongly correlated the performance of the neural network might be degraded. In order to achieve a trade-off the authors propose an algorithm which selects inputs which are more correlated to the output variables and less correlated to already selected input variables. The authors conclude that neural networks that use their input selection method outperform other neural networks with regards to prediction performance for stock market time series forecasting.

Chen et al. (2003) use a probabilistic neural network (PNN) to forecast the direction of returns for the Taiwan stock index. The authors use economic state variables like bond rates, interest rates, lagged index returns, consumption levels, gross national and domestic products, consumer price index and industrial production as input parameters for the neural network. The forecasts are used in a trading strategy and the results are compared to forecasts made by the generalised methods of moments (GMM) with Kalman filter, buy-and-hold strategy and random walk model. The results show that the PNN outperforms the alternative forecasting strategies in terms of expected returns.

Chen, Chianglin & Chung (2001) use neural networks to explore arbitrage opportunities in the Nikkei 225 index. The authors use several technical variables indicating the difference between the spot market and futures market, the difference between two successive periods and changes in the basis. The authors state that the profitability of the proposed model is superior compared to returns from the traditional cost-of-carry model.

Neural networks are very powerful in discovering non-linear relationships in time series data. Yen et al. (2007) analyse the trend of the price spread between the Taiwan Stock Exchange Electronic Index Futures (TE) and Taiwan Stock Exchange Finance Sector Index Futures (TF). The authors explore different trading models and find that the back-propagation neural network model is superior to the genetic programming model during the analysed period. The authors conclude that it is possible to generate profits trading the spread between the two described index futures and suggest a back-propagation neural network with a momentum trading strategy as the best choice amongst the examined models.

Shen, Fan & Chang (2007) propose a tapped delay neural network (TDNN) with an adaptive training and pruning algorithm. It is stated the a good neural network architecture is important for making accurate forecasts and the design is tested using data from the Shanghai Composite Index. The authors report that through the pruning algorithm, the network complexity can be greatly reduced while the prediction precision is improved. The authors argue that the removal of unnecessary network nodes leads to a network with greater generalization abilities.

Roh (2007) develops a neural network based forecasting model for the prediction of volatility in the KOSPI 200 index. The experiments performed by the author show that a neural network combined with an EGARCH model performed best during the analysed period. The authors state that a good forecasting model is essential for risk management and portfolio allocation and conclude that their model performs well in regards to the deviation and direction of forecasting accuracy.

Zhu et al. (2008) analyse the role of trading volume in the context of stock index prediction with neural networks. In the study, the prediction performance under short-, medium- and long-term forecasting horizons is evaluated. The authors state that recent studies show a significant bidirectional non-linear relationship between return and trading volume. The methodology employed involves training neural networks using price and volume data from the NASDAQ, DJIA (US) and STI (Singapore) indices. The empirical results show that a modest improvement in the medium- to long-term time-frames can be achieved when trading volume is considered as an additional input. In contrast to the other time-frames, the authors state that trading volume cannot significantly improve trading performance under the short-term horizon.

Hanias et al. (2007) use back-propagation neutral networks to predict the Athens stock index. The authors use an architecture with one hidden layer consisting of seven hidden neurons and report a good prediction performance in terms of the mean squared error (MSE) up to nine days ahead.

Bekiros & Georgoutsos (2008) use recurrent neural networks to create a trading algorithm for the NASDAQ composite index. In particular, the authors analyse the profitability of a trading strategy which uses the direction-of-change forecast generated by the neural network. A positive forecast leads to a long position being entered, while a negative forecast leads to a short position being entered. Conditional volatility is used as an input for the neural network and compared to the buy&hold strategy as well as the neural network strategy without the conditional volatility as input. The authors report that the best performing model is the one incorporating conditional volatility. The authors list the 'volatility feedback' theory and the existence of portfolio insurance schemes as possible explanations for their findings.

Liao & Wang (2010) examine the statistical properties of movements in several stock indices in the Chinese stock market. The authors use a stochastic time effective neural network which uses lagged index data as inputs and put more weight on recent observations and less weight on older observations. It is argued that the model represents the way investors analyse the market data and that nearer historical data has a stronger impact on future market movements. The authors report a good performance in terms of the forecasting error for the time effective neural network model.

Faria et al. (2009) compare the forecasting performance of neural networks to the adaptive exponential smoothing method in the Brazilian stock market. The authors state that the neural network performs better than the adaptive exponential smoothing method and that a hit rate of correct direction forecasts of 60% is reached. Additional tests reveal that the results are also consistent across more developed markets. The authors conclude that a good forecasting performance can be used to develop profitable investment strategies and that their model is suitable for creating a decision support system for the Brazilian market.

Kara et al. (2011) try to predict the direction of change in the Istanbul Stock Exchange (ISE) National 100 Index. In the study, two forecasting models are developed. The first model is based on artificial neural networks and the second model employs support vector machines. The simulation results show that the neural network performs with 75.74% correct directional forecasts performs better than the support vector machine with 71.52%. The authors conclude that both models show a significant forecasting performance and that both are useful tools in the area of stock index prediction.

Kumar et al. (2011) state that ANNs perform well in noisy environments like stock market data and have a high tolerance to imprecision. These characteristics make ANNs suitable for the use in the area of stock market forecasting. The study compares a feed forward neural network to a radial basis function network and finds that the feed forward architecture has a superior performance. It is concluded that the analysed feed forward ANN is suitable for making informed investments decisions in the share market.

2.3.3. Evolutionary Optimisation Techniques

Han (2006) defines evolutionary optimisation techniques as algorithms that attempt to emulate natural evolution. This is achieved by creating a random set of rules which try to generalize data. The best performing set of rules is kept (survival of the fittest) and then changed (mutated), and multiplied to create a new set of rules. This process is repeated in order to find a set of rules that best matches the given dataset.

Evolutionary optimisation techniques have also been used in the recent literature to forecast the movements of stock indices, although their popularity has not been as large compared to artificial neural networks.

For example, Kim et al. (2006) use genetic algorithms to combine multiple classifiers to predict the Korea stock price index. The classifiers used consist of a number of different technical indicators. The authors describe a number of combination techniques with a majority vote being the most simple combination method. The authors report that the proposed genetic algorithm based method forecasts the index more precisely that any other of the analysed combination methods. Therefore, it is argued that genetic algorithms pose an effective decision tool for unstructured business problems like stock index forecasting.

Majhi et al. (2008) propose a clonal particle swarm optimization technique to predict the S&P 500 and DJIA indices. The performance of the model is compared to a standard particle swarm optimization technique and to genetic algorithms. The performance is measured in terms of computational complexity, learning rate, minimum MSE, training time and prediction accuracy. The simulation results show that the clonal particle swarm optimization model performs best out of the three analysed techniques. The authors conclude that the proposed model is a suitable candidate for short- and long-term stock index prediction.

In a later study, Majhi et al. (2009) refine the forecasting model using adaptive bacterial foraging optimization. Compared to the particle swarm optimization and genetic algorithm models, the adaptive bacterial foraging optimization is more accurate and shows faster convergence.

2.3.4. Hybrid Models

Hybrid forecasting models combine ANNs with other optimization techniques to further enhance the forecasting performance. In recent literature, hybrid models are becoming increasingly popular in the domain of stock index forecasting.

Zhang et al. (2007) use an ensemble of particle swarm optimisation (PSO) and artificial neural networks to forecast the Nasdaq 100 and the S&P CNX Nifty stock index. The proposed algorithm creates several neural networks through bagging and trains the networks using a PSO algorithm. The best networks are then selected and combined. The simulation results indicate that the proposed algorithm is effective and performs better than the benchmark model represented by an genetic algorithm based selective ensemble algorithm.

Fu et al. (2007) explain that the volatile nature of stock market movements makes it necessary to quickly adapt to changing market conditions. This means that in addition to an accurate forecasting performance, a fast learning capability is needed so that the model can be retrained in a short period of time. The authors propose a combination of a fuzzy cerebellar model articulation controller with a Bayesian Ying-Yang neural network. The model is based on the Chinese Ying-Yang philosophy which says that everything in the world is a result of the conflicting opposites, Ying and Yang. The perfect state is achieved when Ying and Yang are in harmony. In terms of the forecasting model, the authors express Yang as forward/training model and Ying as backward/running model. According to the authors, harmony between Ying and Yang is reached when the trade-off between the two models is reached which leads to the forecasting model with the highest overall generalisation capability. The model is tested on the Spanish Ibex35 index shows an accurate prediction performance. In addition, a high learning speed and a low memory requirements are reported.

Wang & Nie (2008) evaluate the performance of several forecasting models for four different stock indices of the Shanghai stock market. The authors start by analysing the prediction accuracy of a grey model, back propagation neural network and support vector machine in isolation. Then the models are combined employing several combining methods. The neural network based combination method performs better in terms of average effectiveness and standard deviation than the support vector machine based combination method. However, even the worst combination method performed better that the corresponding single model so that the authors conclude that a combination of the mentioned forecasting models can greatly improve forecasting effectiveness.

Huang & Wu (2008) develop a hybrid forecasting model consisting of a genetic algorithm based optimal time-scale feature extraction algorithm and a support vector machine. The input time series is decomposed employing wavelet analysis and genetic algorithms are used to extract the optimal time-scales from the decomposed features. The resulting subsets are then used as input for a support vector machine. The simulation study uses neural networks, simple support vector machines and GARCH models as benchmarks. The simulation results indicate that the proposed model can significantly reduce the forecasting error relative to the analysed benchmark models.

Jia et al. (2008) combine multi expression programming (MEP), particle swarm optimization and artificial neural networks to forecast the S&P CNX Nifty stock index. The authors state that MEP is a variation of genetic programming. ”A traditional GP encodes a single expression (computer program). By contrast, a MEP chromosome encodes several expressions. The best of the encoded solution is chosen to represent the chromosome.” (Jia et al. 2008, p.31) The authors conclude that the proposed model is feasible and effective for stock index forecasting problems.

Wu et al. (2008) propose an ensemble of artificial neural networks and support vector machines to predict movements in stock market indices. The two machine learning techniques are combined using a linear approach and particle swarm optimisation. The authors state that a combination of these techniques performs significantly better than using each technique individually.

Zhang & Wu (2009) use the structure of a backpropagation ANN and enhance the updating process of the network weights employing bacterial chemotaxis optimization. The enhanced model is applied to S&P 500 index data and the results are compared to a standard backpropagration ANN. The experiments conducted by the authors show that the proposed model offers less computational complexity, increased forecasting accuracy, and faster training time.

Zhi et al. (2009) state that traditional methods for selecting inputs for stock index prediction are subjective and the forecasts are ineffective. The authors propose to use principal component analysis to choose input parameters. The forecasting model consists of a combination of genetic algorithms with neural networks. It is argued that genetic algorithms can overcome local convergence so that they are more suitable than traditional approaches in determining the neural network weights. The authors conclude that the proposed model increases prediction accuracy.

Shen et al. (2011) use an artificial fish swarm algorithm to optimise a radial basis function neural network in order to predict stock indices in the Shanghai stock market. A simulation study is performed and the results are compared to neural network forecasts optimized by genetic algorithms and particle swarm optimization. In addition, the results are compared to forecasts made by ARIMA models, backpropagation networks and support vector machines. The study shows that, although not having the the highest forecasting accuracy, the proposed artificial fish swarm algorithm has a good forecasting performance. The major advantage of the algorithm is that the optimization is suitable for parallel computation since it is independent of initial values.

2.3.5. Analysed Markets

Stock index forecasting requires large data sets. In the recent literature, the most often analysed stock indices are the US based indices.

For example, Majhi et al. (2008) use particle swarm optimisation to forecast the S&P 500 and Dow Jones Industrial Average (DJIA) indices. Collard & Ades (2008) examine the sensitivity of US indices to commodity prices. In particular, the following list of US indices is analysed: Dow Jones (DJ) Industrial Average, DJ Transportation Average, DJ Utility Average, S&P 500, S&P 100, Nasdaq 100, S&P 400 MidCap, and S&P Small Cap 600 Index. Huang & Wu (2008) use a combination of genetic algorithms and support vector machines to forecast a number of global stock indices including the Nasdaq 100. Chu et al. (2009) also try to predict the Nasdaq 100 index using a fuzzy dual-factor time series model. Liao & Wang (2010) employ a stochastic time effective neural network to forecast Taiex and Nadaq 100 indices. Zhu et al. (2008) use neural networks to forecast the Nasdaq 100, DJIA and Straits Times Indices. Bekiros & Georgoutsos (2008) also examine the Nasdaq 100 index with recurrent neural networks.

Using US data has the advantage the market is well established, there is enough trading liquidity and data is readily available for research purposes.

In term of the number of published articles, the quantity of research interest in the US market is followed by the Chinese, Taiwanese, Japanese, and Indian stock markets.

Chen & Li (2006), Zeng & Zhang (2006), Shen, Fan & Chang (2007), Wang & Nie (2008), Niu et al. (2008) and Ning et al. (2009) model the Chinese stock market. Leung et al. (2000), Lee & Chen (2002), Jaruszewicz & Mandziuk (2004), Huang et al. (2005) and Lu et al. (2009) forecast the Japanese stock index. Chen et al. (2003), Huarng & Yu (2005), Cheng et al. (2006) and Chu et al. (2009) examine the Taiwanese stock exchange. Abraham et al. (2003), Chen et al. (2005), Zhang et al. (2007), Jia et al. (2008) and Wu et al. (2008) build models to predict the Indian stock market.

The stock index forecasting literature also includes studies from Spain (Perez-Rodriguez et al. 2005) (Fu et al. 2007), Brazil (Faria et al. 2009), Italy (Armano et al. 2005), UK (Leung et al. 2000), Australia (Pan et al. 2005), Greece (Hanias et al. 2007), Singapore (Zhu et al. 2008), Tunisia (Slim 2004) and Poland (Witkowska & Marcinkiewicz 2005).

The largest number of different datasets is used by Huang & Wu (2008). The study analyses co-movements of stock indices and tries to predict the following daily indices: NASDAQ (US), S&P 500 (US), NK225 (Japan), TWSI (Taiwan), KOSPI (South Korea), CAC40 (France), FTSE100 (UK), DAX30 (Germany), MIB40 (Italy) and TSX60 (Canada).

The literature shows that there exists a lead-lag relationship between large and small economies. ”In general, well established stock index values and exchange rates are used by researchers who try to forecast emerging markets. That indicates that emerging markets are greatly influenced compared to well established markets.” (Atsalakis & Valavanis 2009, p.5936)

The majority of literature tries to forecast the stock index directly. Only a limited number of studies (Hamid & Iqbal 2004, Witkowska & Marcinkiewicz 2005, Kim 2004) use stock index futures data.

In contrast to the stock index itself, stock index futures can actually be traded.

2.3.6. Input Variables

Selecting the right input variables is very important for machine learning techniques. Even the best machine learning technique can only learn from an input if there is actually some kind of correlation between input and output variables.

The most commonly used parameters in the literature are daily opening, high, low and close prices. Also often found are technical indicators which are mathematical transformations of lagged index data. The most common technical indicators used in the surveyed literature are the simple moving average (SMA), exponential moving average (EMA), relative strength index (RSI), rate of change (ROC), moving average convergence / divergence (MACD), William’s oscillator and average true range (ATR).

For example, Kim et al. (2006) use the following list of technical indicators as inputs for their evolutionary forecasting approach: moving average, relative strength index, psychology, momentum, stochastic %D, volume ratio, on balance volume, disparity, and rate of change.

Liao & Wang (2010) use the daily opening price, closing price, highest price, lowest price and trade volume as input for their neural network and the output consists of the closing price of the next trading day.

Briza & Naval (2011) select the directional movement index, linear regression, moving average convergence-divergence, moving average and parabolic stop and reverse in their study. These technical indicators are then used as basis for a particle swarm optimization algorithm.

In addition to data purely derived from past index data, some studies use economic data in order to forecast the stock index.

Stansell & Eakins (2004) forecast the change in US based S&P sector stock indices with neural networks. The list of 19 economic variables shown in table 2.1 are used as input parameters.

The authors state that input data needs to fulfil certain criteria in order to be usable in the forecasting process. The information has to be available on a consistent and timely basis, and there should be a rational economic justification for believing that the variable has an effect on the predicted index.

Collard & Ades (2008) analyse the sensitivity of US stock market indices to the commodity prices of the US dollar, oil, and gold. The authors argue that the companies which form a stock index incur capital costs for borrowing funds and energy costs for producing and transporting goods. Capital costs are influenced by the value of the US dollar and energy costs are affected by changes in the major energy commodity, oil. In addition, changes in the gold price are used as a proxy for the belief about future inflation.

1. Capacity utilisation	11. Money zero maturity money stock
2. Consumer sentiment University of Michigan index	12. University of Michigan inflation expectation index
3. Consumer price index	13. National association of purchasing managers index
4. Housing starts	14. Manufacturer's new orders
5. Industrial production index	15. Spot oil price
6. Inventory to sales ratio	16. Yield spread on Treasury securities
7. Composite index of leading indicators	17. S&P 500 stock index
8. Ml money stock	18. Trade weighted exchange rate
9. M2 money stock	19. Civilian unemployment rate
10. M3 money stock	

Table 2.1.: Input variables used by Stansell & Eakins (2004)

Chen et al. (2003) use the spreads of long-term bond yields over short-term bond yields as an input parameter. The authors state that it may have some power to forecast stock returns since this variable has also a business cycle pattern. In general it is stated that an independent variable must be observable (available and published) before the prediction can be made. "Constructing the data set in this manner ensures that the generation of out-of-sample forecasts will be similar to those made in the real world. It is because only observable, but not future unobservable, data can be used as inputs to the forecasting models." (Chen et al. 2003, p.906)

Additional economic variables found in the literature are the unemployment rate (Stansell & Eakins 2004) and the value of US stock indices for non-US studies. Huang et al. (2005) use the S&P 500 data and the USD/JPY exchange rate to predict the NIKKEI 225 index. Jaruszewicz & Mandziuk (2004) also try to predict the NIKKEI index and use data from the US NASDAQ and German DAX indices. Pan et al. (2005) use the S&P 500 index as input to predict the Australian AORD index. Witkowska & Marcinkiewicz (2005) use the USD/PLN exchange rate as well as the US DJIA, German DAX and Japanese NIKKEI indices in order to predict Warsaw index futures.

2.3.7. Performance Metrics

The majority of technical machine learning literature uses some form of forecast error as the benchmark performance metric. The forecast error is the difference between the forecasted and the actual value. Variations of the forecast error used in the literature include the mean absolute error (MAE), the normalised mean absolute error (NMAE), the mean squared error (MSE), the root mean squared error (RMSE) and the mean absolute percentage error (MAPE).

For example, Zhang et al. (2007) use a neural network to predict the Athens stock index and employ the MSE to evaluate the prediction performance. Wu et al. (2008) combine support vector machines and neural networks and use the RMSE to compare the forecasting accuracy to the performance of each forecasting technique by itself without combination. Majhi et al. (2008) use the convergence rate, MSE, training time and MAPE to compare their proposed particle swarm optimisation model to other genetic algorithm based techniques.

Niu et al. (2008) compare forecasts made by the grey model, neural network and support vector machine using the MRE and MSE. Huang & Wu (2008) analyse support vector machines enhanced with genetic algorithms to pure support vector machines and use the RMSE as performance metric. Ning et al. (2009) compare chaotic neural networks to backpropagation neural networks employing the relative forecasting error.

Leung et al. (2000) argue that a prediction with little forecast error does not necessarily translate into capital gain.

”Depending on the trading strategies adopted by investors, forecasting methods based on forecast error may not be adequate to meet their objectives. In other words, trading driven by a certain forecast with a small forecast error may not be as profitable as trading guided by an accurate prediction of the direction of movement (or sign of return.) Therefore, predicting the direction of change of the stock market index and its return is also significant in development of effective market trading strategies." (Leung et al. 2000, p.174)

Thawornwong & Enke (2004) also state that the forecast performance based on the sign measure matches more closely to the profitability performance than do traditional criteria.

The hit rate is a metric that measures the percentage of times that the direction of change is forecasted correctly. Zhu et al. (2008) analyse component based neural networks and use the hit rate to evaluate the neural network.

Recent studies show that it is common to use a number of different metrics to evaluate the forecasting performance of the analysed machine learning technique in relation to the benchmark models. Lu et al. (2009) use the RMSE, normalized MSE, MAD and directional symmetry as metric when comparing a support vector regression based model to other benchmark techniques. Faria et al. (2009) compare a neural network based model to an adaptive exponential smoothing technique in terms of the RMSE and directional prediction accuracy.

Further evaluation metrics are the simulated trading returns and the Sharpe ratio. The Sharpe Ratio is a measure for the excess return per unit of risk in a trading strategy. The Sharpe Ratio is employed as a evaluation metric by Perez-Rodriguez et al. (2005), Armano et al. (2005) and Bekiros & Georgoutsos (2008).

2.4. Conclusion

This section summarises the findings of the literature review and reveals gaps in the literature. Based on the gaps, the research question is developed. In addition, the contribution of this thesis is highlighted.

2.4.1. Gaps in the Literature

The literature review has revealed that a large range of publications exist in the area of stock index forecasting using machine learning techniques. The two main reasons quoted in the literature to justify the research are the improvement of trading performance and the usefulness of index forecasting in the domain of portfolio hedging. With regards to portfolio hedging however, there are very few index forecasting papers that analyse portfolio hedging and consider realistic conditions like trading costs and slippage.

In the recent literature, variations of ANNs and hybrid systems are very popular. There is a clear trend to use established ANN models and enhance them with new training algorithms or combine ANNs with emerging technologies into hybrid systems.

It has been shown that dynamic hedging is important in order to protect funds against unfavourable moves in the stock market. Exact measures as to when and how long the hedging should occur have not yet been established. This leads to an interesting problem in the area of decision sciences. It needs to be analysed whether machine learning techniques can enhance the decision process in the domain of stock index futures hedging.

In addition, the accuracy of the prediction method is often measured in terms of expected trading returns or forecasting errors. There is a lack of machine learning papers which actually test if the prediction technique leads to an increase in hedging effectiveness.

Adding to the complexity of the problem is the fact that futures data consists of individual contracts and is not continuous. It needs to be determined how machine learning techniques can be trained using non-continuous contracts. The literature review has also shown that there is no defined methodology for creating and benchmarking hedging strategies based on machine learning techniques.

2.4.2. Research Question and Contribution

Based on the gaps found in the literature, the following research question is proposed:

”Can artificial neural networks be used to improve the effectiveness of dynamic hedging strategies in the Australian stockmarket?”

In answering the research question and addressing the gaps mentioned earlier, this thesis contributes to the body of knowledge as outlined below:

- Showing whether machine learning techniques can be used to enhance the hedging effectiveness of risk management strategies.

- Contribute a methodology for building and testing hedging strategies using ANNs by extending the methodology of Vanstone & Finnie (2009) to the domain of portfolio risk management

- Development of an early stopping algorithm for neural network training based on financial metrics (e.g. Sharpe Ratio) instead of statistical metrics (e.g. MSE)

3. Methodology

3.1. Introduction

This chapter discusses the methodology employed in this thesis. In particular, the process of creating and benchmarking selective hedging strategies is described. In addition, related issues regarding data adjustment, variable selection, and the software used are presented.

The literature review has revealed a number of gaps in the financial machine learning literature. It has been shown that futures data consists of non-continuous contracts that exhibit unique characteristics which have not been addressed by previous research.

In addition, it has been pointed out that there is the need for risk management strategies in the Australian stockmarket to avoid the effects of events like the global financial crisis.

The aim of this research is to fill this gap by proposing a machine learning enhanced decision-support system that allows hedgers to maximise their expected return while practising the hedge against spot price uncertainty.

Figure 3.1 gives a high level overview of the methodology used in this study.

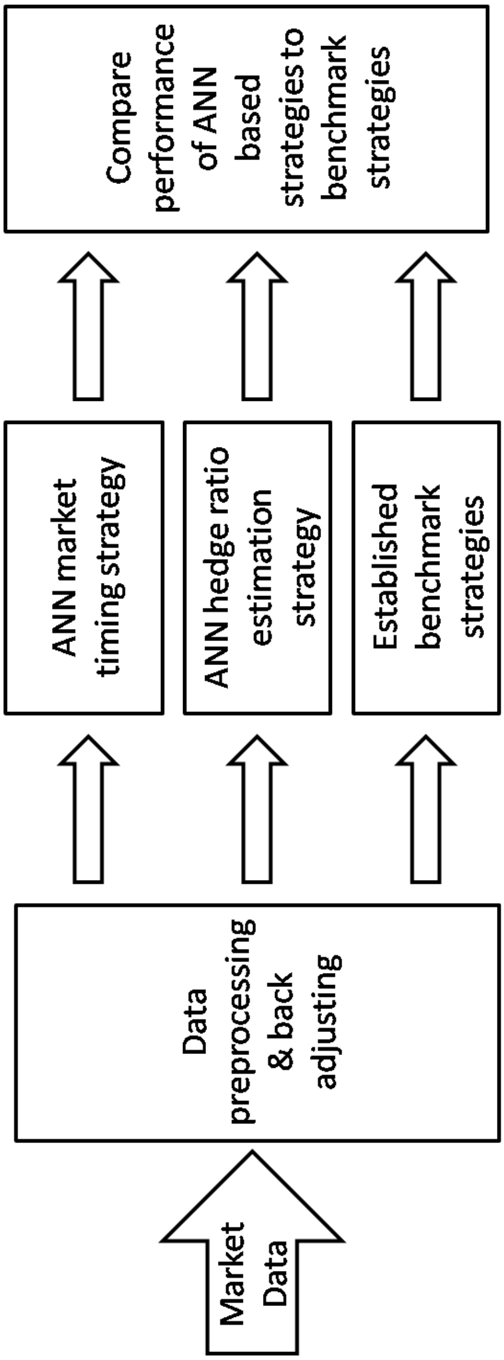

Figure 3.1.: Methodology Overview

The methodology for creating and benchmarking neural network based hedging strategies consists of the following number of steps.

1. Create and preprocess datasets

2. Create an artificial neural network based decision support system to signal volatile market conditions (market timing ANN)

3. Create and benchmark a hedging strategy based on the market timing ANN

4. Create an artificial neural network based decision support system to forecast the hedge ratio (hedge ratio ANN)

5. Create and benchmark a hedging strategy based on the hedge ratio ANN

The first step is the creation and preprocessing of the datasets. Since futures data consists of individual contracts which expire several times a year, a continuous data series needs to be created. Furthermore, information from various data sources is merged into one large dataset, so that all required information is available for simulation purposes. The description of data and the back adjusting process is detailed in section 3.3.

The next step involves the training of the market timing ANN. The market timing ANN is an artificial neural network which has the purpose of notifying a risk manager of volatile market conditions. Based on the predictions of the resulting network a selective hedging strategy is derived. This strategy is then compared to established hedging strategies found in the literature so that an assessment regarding the benefits of the described strategy can be made.

The process is then repeated to create a hedging strategy which determines a suitable hedge ratio and the benefits of the strategy are evaluated. Both ANN based hedging strategies are described in detail in section 3.2.

After passing through the described list of steps it is possible to draw conclusions regarding the proposed research questions. In particular, it is possible to assess whether artificial neural networks are suitable decision support tools in the domain of stock portfolio hedging.

3.2. ANN based hedging

Figure 3.2.: Stock Portfolio

Events like the global financial crisis showed that investing in the stock market can potentially lead to high losses for the holder of common shares. Company specific risk can be reduced by diversification. However, systematic market risk that affects the whole stock market can have a large negative impact on portfolio returns. Derivatives based on the stock index, like stock index futures, can be used to protect a portfolio against unfavourable moves in the stock market. In this study, a market timing model based on artificial neural networks is developed.

Figure 3.2 shows the value of a sample portfolio from 2000 to 2010. The aim of hedging is to reduce the risk which is associated with large downside price movements in the market. Figure 3.3 illustrates an idealised hedge timing strategy that could have protected the portfolio against large downturns. The downward pointing arrows indicate when a hedge could have been established and the upwards pointing arrows indicate when the hedge could have been released.

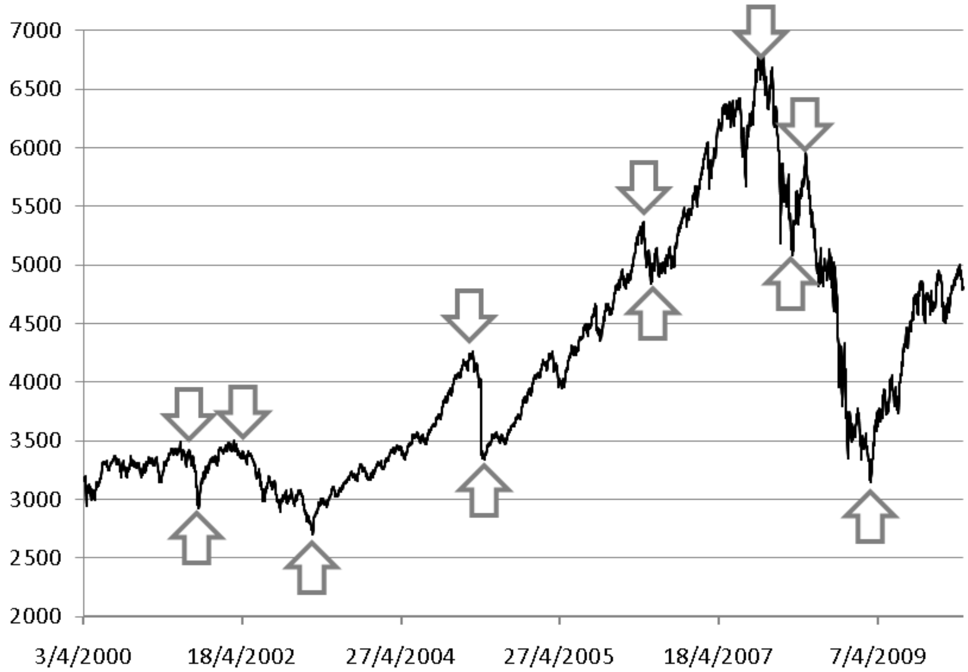

Figure 3.3.: Hedge Timing (Example)

Of course, a good timing is easy to determine in hindsight. Forecasting the optimal hedge timing in advance is very challenging.

The aim of this study is to evaluate if machine learning techniques are suitable tools to assist in the process of making portfolio hedging decisions.

3.2.1. Market timing ANN

Figure 3.4 shows a flow chart to visualise the hedging process based on an artificial neural network. The market timing ANN analyses market data in regular intervals and forecasts whether volatile market conditions are expected. Based on the forecast a decision is made if the portfolio of stocks should be hedged or not. If it is determined that no hedge is necessary the portfolio of stocks is left unprotected to allow for an upside gain in portfolio value. If on the other hand market conditions are expected to be volatile the portfolio needs to be hedged.

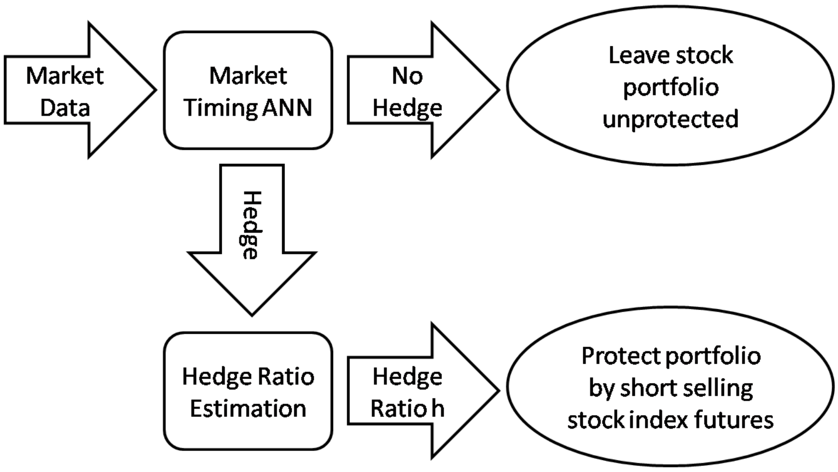

Figure 3.4.: Stock Index Futures Hedging Flow Chart

The next step in the hedging process is the hedge ratio estimation. The hedge ratio is used to determine the number of futures contracts which need to be short sold in order to protect the portfolio. Please refer to section 3.5 for an explanation of the hedge ratio estimation.

3.2.2. Hedge ratio estimation ANN

In addition to the market timing ANN described in the previous section, a second ANN based hedging strategy is proposed in this thesis. The market timing ANN makes a forecast about future market conditions and is then either fully hedged or not hedged at all. The second method of ANN based hedging is shown in figure 3.5. The hedge ratio estimation ANN always hedges the portfolio. Market data is evaluated on a regular basis and then the hedge ratio is calculated based on the output of the ANN. The ANN output ranges from 0 to 1, where 1 means that the portfolio is fully hedged and 0 means that the portfolio is not hedged at all. The benefit of this model is that the hedge ratio can be adjusted based on the strength of the ANN signal. For example, an output of 0.2 is a weak signal and only 20% of the portfolio is protected by the hedging strategy whereas 0.8 is a strong signal and 80% of the portfolio would be protected.

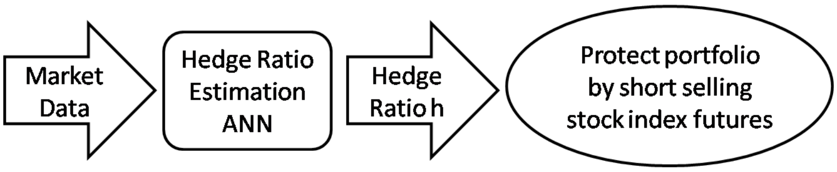

Figure 3.5.: Hedge Ratio Estimation ANN Flow Chart

By comparing the hedge ratio estimation ANN to the market timing ANN strategy it is then possible to draw conclusions if it is beneficial to consider the strength of the ANN signal compared to the "all or nothing" approach.

3.3. Data

This study uses 10 years of end-of-day data beginning in May 2000, when the SPI 200 contract had been first listed, to April 2010. The objective of this thesis is to evaluate whether viable selective hedging strategies can be developed using ANNs. These strategies are evaluated in the context of the Australian stock market. Therefore most of the analysed data originates from the Australian Securities Exchange (ASX). The ASX is the result of the merger of the Australian Stock Exchange and the Sydney Futures Exchange. In addition, overseas data is used in order to analyse inter-market influences on the Australian stock market. In the following, the sources of data, preprocessing steps and merging of datasets are described in detail.

3.3.1. Sources of data

Figure 3.6 gives an overview of the dataset creation for this study. The data is sourced from the Securities Industry Research Centre of Asia-Pacific (SIRCA 2010) and the Reserve Bank of Australia (RBA 2010). The majority of data is sourced from SIRCA. All futures data is preprocessed and back adjusted as described in section 3.3.2. The futures dataset is then merged with the other data from SIRCA and the interest rates information from the RBA. The merging process is detailed in section 3.3.3.

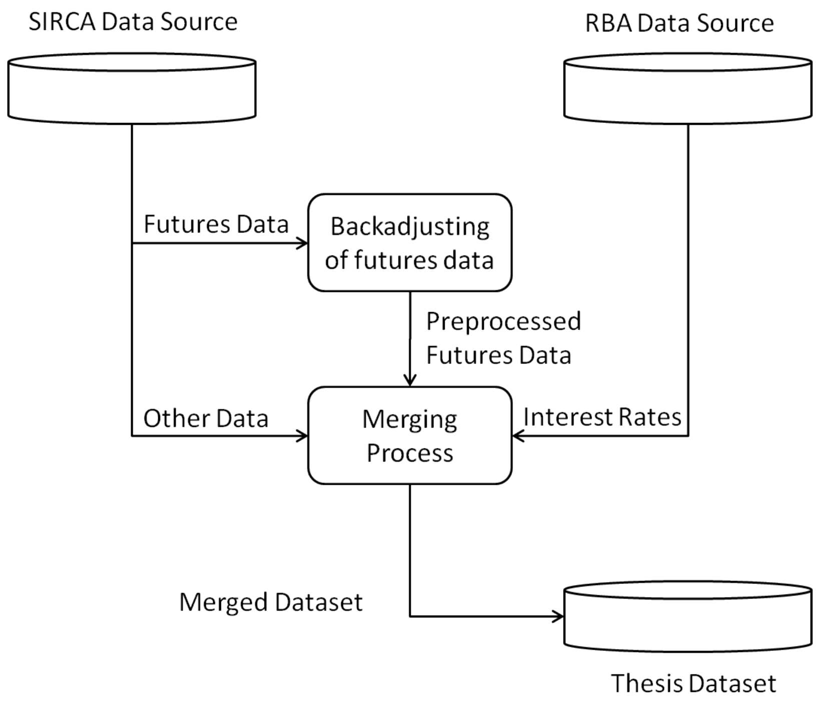

Figure 3.6.: Overview of the dataset creation

3.3.1.1. Content of SIRCA dataset

The SIRCA dataset consists mainly of futures contracts and sector indices. The dataset requested from SIRCA has been delivered in one large comma separated (CSV) file which includes all requested timeseries information. The first step of data processing involves the separation of the individual dataseries into separate files. Each dataseries is saved in a file where the filename corresponds to the series symbol and the file ending '.csv'. For example, the SIRCA Symbol used for the S&P/ASX 200 stock index is .AXJO and all information related to that index is stored in a file called .AXJO.csv. In the case of futures data the splitting process is slightly more complex. As explained in the literature review, futures data consists of individual contracts which expire several times a year. Every futures contract has a symbol compromising of a base code and the expiry date information. For example, the SIRCA code for the Australian SPI 200 futures contract is YAP. The expiry month is encoded according the conventional letter codes listed in table 3.1. The expiry year is encoded as single digit. For example, the SPI 200 futures contract expiring in September 2009 has the symbol YAPU9 and the contract expiring in December 2011 has the symbol YAPZ1.

Code	**Month**
F	January
G	February
H	March
J	April
K	May
M	June
N	July
Q	August
U	September
V	October
X	November
Z	December

Table 3.1.: List of letters used to encode futures delivery month

A problem with the naming scheme used by SIRCA/Reuters is that codes are reused after a certain period of time. For example, the contracts expiring in December 2000 and

December 2010 share the same symbol YAPZ0. This poses a problem for the historical simulation since it needs to be determined to which decade a contract belongs. In order to solve this problem an algorithm has been developed which expands the 1 digit year to a 4 digit representation based on the trading date. Since this study does not use any data before the year 2000, 2000 is used as the base date. E.g. if the SIRCA dataset contains a trading record with the symbol YAPZ0 it is first attempted to assign this record to the year 2000 which is the result of adding the base date 2000 and the single digit year representation which is zero is this case. Then the actual trading date of the record is compared to the expiry year. E.g. if the trading date was 02/05/2000 then the trading date would be in the timespan which precedes the end of the year 2000 so that 2000 is assigned as expiry year for the examined trading record. If the trading date was 19/06/2009 then the trading date would be after the calculated expiry year of 2000. In this case 10 is added to the calculated year in order shift the expiry year by one decade. The date 19/06/2009 precedes the end of year 2010 so that the trading record is assigned to the expiry year 2010. The result of the described procedure is that the two uniquely identifiable symbols YAPZ2000 and YAPZ2010 are created out of the ambiguous symbol YAPZ0. The corresponding data is then stored in files named YAPZ2000.csv and YAPZ2010.csv The process is repeated for all futures contracts so that a consistent naming scheme is implemented. All the software used in this study uses the described naming scheme to access information related to futures contracts.

The content of the SIRCA dataset is shown in Table 3.2. The dataset consists of several stock indices and futures contracts which are used as inputs for the neural network training. The shown contracts have been selected based on the literature review.

Each dataseries described in table 3.2 consists of daily open, high, low and close prices. In addition, futures time series contain a field called open interest. Open Interest is the total number of open futures positions in a market that has been entered into and not yet sold by an offsetting transaction. It gives an indication of the liquidity of the market. In contrast to the trading volume, which is the number of trading transactions made during a day, the open interest just shows the open positions.

SIRCA Series Name	**Description**
ASX/S&P 200 Index	Australian Standard & Poor's 200 Stock Index
S&P 500 Index	US Standard & Poor's 500 Stock Index
Australian Dollar Exchange Rate	Exchange Rate between the Australian dollar and the US dollar
Oil Futures	Light crude oil futures contracts (CL)
Gold Futures	100 oz gold futures contracts
SPI 200 Futures	SPI 200 index futures
Sector Indices	Indices for the Australian energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, telecommunication services and utilities sectors (see section 3.3.5 for details).

Table 3.2.: Content of SIRCA dataset

When the data is imported into the database, a validity check is performed in order to filter out invalid data records. The following list show the criteria used for validity checking.

- High >= Open
- High >= Close
- Low <= Open
- Low <= Close
- High >= Low

In addition, it is checked that all values are different from zero.

3.3.1.2. Content of RBA dataset

The data sourced from the Reserve Bank of Australia consists of the short term and long term interest rates. The literature review revealed that the spread between movements in the short term interest rate and long term interest rate may give valuable insights into the state of the stock market. (Chen et al. 2003)

In order to evaluate the spread of short term and long term interest rates, the 90 day bank accepted bills interest rate is used as a proxy for short term interest rates and the 10 year Australian government bonds interest rate as a proxy for long term interest rates.

RBA Series Name	**Description**
90 day interest rate	90 day bank accepted bills interest rate represents the short term interest rate.
10 year interest rate	10 year Australian government bonds interest rate represents the long term interest rate.

Table 3.3.: Content of RBA dataset

3.3.2. Backadjusting Futures Data

As discussed in the literature review, there is no single continuous series of futures prices. Futures markets are comprised of individual contracts that have different expiry dates in the future. One way to represent the history of a futures market is to splice individual contracts together. However, it is important to understand that a spliced contract is just a representation of the history of a market.

The most popular method for splicing contracts together is the 'spot month' method. In order to get a single continuous contract, the data is always taken from the contract nearest to expiry. Figure 3.7 shows a simple spliced continuous time series. One problem with spliced data is that when one contract expires, the next contract might trade at another price level which leads to gaps in the time series. The gaps do not represent actual jumps in the futures price, but rather differences in the price level of two different contracts. The main problem with the gaps is that a computerised system might interpret the gap as profit or loss. (*Norgate Investor Services* 2011)

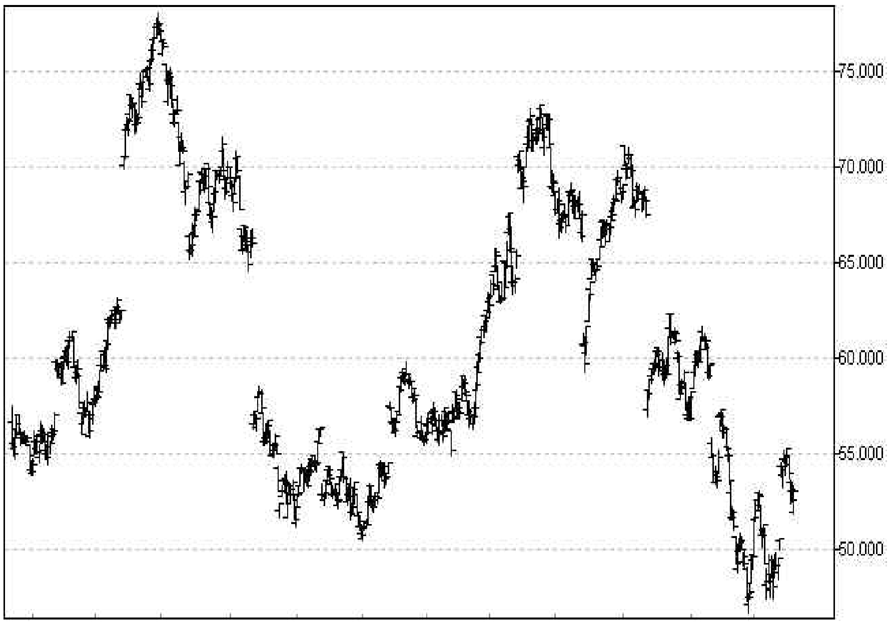

Figure 3.7.: Spliced Continuous Contract

A solution to overcome the problem of gaps in the time series is to adjust the price levels of the contracts. Figure 3.8 shows the spliced futures contract on the left and the back-adjusted version on the right. The back-adjustment retains the price level of the current contract and adjusts the levels of the previous time series so that the gaps are eliminated. The time series can now more easily be analysed by computerised systems. However, the price levels do not represent the real historical price levels anymore and prices can even become negative due to the back-adjustment.

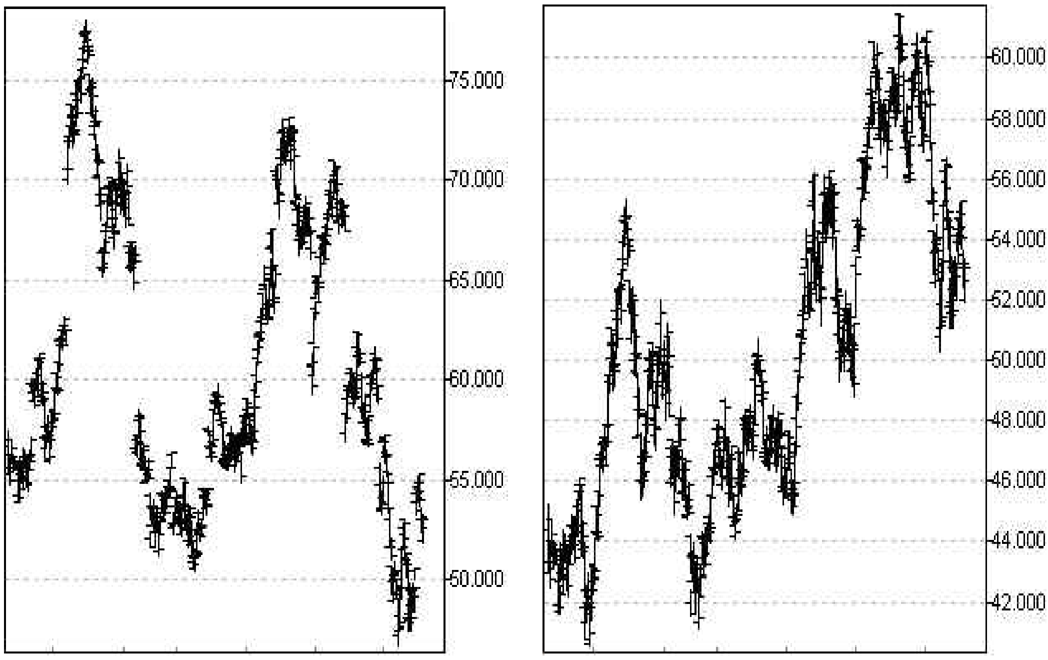

Figure 3.8.: Spliced Contract vs. Back-adjusted Contract

Two important choices need to be made when creating a continuous time series. First, a point in time needs to be selected (the rollover date) when to switch from the maturing contract to the next. Second, a method of adjusting differences in the price levels between two contracts needs to be determined.

3.3.2.1. Selecting Rollover Dates

Ma et al. (1992) point out that there does not appear to be a unique way of determining when to switch from one contract to the next for all purposes. The authors state that the most common methods of rolling over used in the literature include switching at the delivery date, the first notice date, or some arbitrary length of time before the delivery date. The simplest method of rolling over is switching to the new contract on the expiry date of the contract. However, the open interest begins to decline as the delivery day for a contract nears. Traders begin to close their positions in the nearby contract and open new positions in the next nearby contract to avoid problems associated with illiquid trading.

Therefore futures contracts are rolled over at some arbitrary time before the delivery date, e.g. the first day of the delivery month or the last trading day of the previous month.

The liquidity of a futures contract is characterised by a high level of trading activity. A high liquidity is important because futures can be bought or sold in the market without affecting the futures price.

Liquidity in the market can be observed by the volume of contracts traded and by the open interest. Carchano & Pardo (2009) state that the open interest is considered by many traders as a more reliable indicator of liquidity than volume. In this study, the contract with the highest liquidity as observed by the open interest is selected as the most relevant contract. It is switched from the expiring contract to the second to expire contract the day after a higher open interest in the second contract can be observed compared to the first one. Constructing the continuous time series this way ensures that liquidity problems would have been avoided historically.

3.3.2.2. The Adjustment of the Price Levels at the Rollover Date

Another important aspect to consider is the price level of the futures contracts at rollover date. There are three main ways of dealing with different price levels in the literature:

- Splicing of contracts
- Subtracting price levels
- Ratio adjustment

The price levels of two contracts trading at the same time might be different at the rollover date. For example, the December contract could trade at 4480 index points whereas the March contract could trade at 4500 points. If a trader decides to rollover, he would close the position in the December contract and open a position in the March contract. The simplest method of creating a continuous contract is called ”splicing”. This involves using the old contract data until the rollover day and using the next contract from the rollover day onwards. However, this would mean that there is an artificial jump in the price level of 20 index points at the rollover date. This jump would not translate into an equity gain for a trader since he had to sell the contract at the old price level and buy at the new price level. These artificial jumps can bias backtesting results.

Ma et al. (1992) state that some traders prefer contracts with no adjustment for price differences made, since only real transaction prices can be used in practice. However, if an adjustment is needed, a common way is to take the difference in the price levels between the new contract and the old contract, at each rollover date, and add the difference to the previous prices. By adjusting price levels backward in time, the price gaps resulting from contract rollover are eliminated. Since there is an adjustment on all prior prices at each rollover date, most prices have a number of price gaps subtracted from them. These multiple subtractions can sometimes lead to the effect that historical prices become negative in the backadjusted series. Equation 3.1 shows how the adjustment at rollover is performed using the subtraction method. P_1 is the unadjusted price of the old contract and P_{1Adj} represents the adjusted price. C_2 is the close price of the new contract and C_1 the close price of the old contract at the rollover date.

$$P_{1Adj} = P_1 + (C_2 - C_1) \tag{3.1}$$

The subtraction method leaves the absolute daily price changes intact, but introduces an error when returns are computed in percentage form. For example, if a historical contract has a price change from 3400 to 3434 index points in one day, this would mean a gain of 1%. When the trader rolls over into a new contract, a price adjustment for the historical contract needs to be made. If e.g. a price difference of 50 index points is subtracted from the historical contract, the historical prices become 3350 and 3384 which would mean a theoretical gain of 1.01%. As prices approach zero or become negative because of multiple adjustments, these measurement errors become even more significant. This is especially a problem when using technical indicators and neural networks since both techniques rely to a great extent on percentage calculations.

An alternative to the subtraction method is the ratio method. Instead of subtracting the price levels, the difference of the closing prices at rollover date is calculated in percentage terms as shown in equation 3.2.

$$P_{1Adj} = P_1 * (1 + \frac{C_2 - C_1}{C_1}) \tag{3.2}$$

Constructing the continuous contract this way resembles more the way a trader would sell a contract at the rollover date and buy again at a different price level. Holton (2003) uses a similar approach which he calls return-adjustment. The author states that prior to the most recent rollover date, the adjusted price levels may not reflect actual price levels or actual price changes. Some traders argue that the ratio adjustment leads to fractional index values, which cannot be observed when implementing a strategy since the minimum price movement for the SPI 200 contract is one index point. The advantages of using this backadjustment method are that prices will not become negative, and historical returns will be correctly represented.

As outlined above, every method of backadjustment has its advantages and disadvantages. The most popular method of backadjustment in the literature is the subtraction method, since it removes gaps in the price series and keeps actual price levels intact. However, problems arise if the time series is used for percentage calculations.

In this thesis, a different approach is proposed. Instead of picking the least objectionable option, two continuous time series are created. The first continuous contract is built by simply splicing individual contracts together, so that real transaction prices are kept intact. The spliced contract is then used for trading simulations. Artificial price jumps are avoided by closing a position at the rollover date and opening a new position in the new contract, like a trader would do when he had to rollover a position. The second continuous contract is created using the ratio backadjustment method. This time series is solely used for the calculation of technical indicators and as input for the neural networks. It is important to remember that a continuous contract is just a representation of what historically happened in the futures market. Using the two described contracts in combination has the advantage that real transaction prices can be used for the simulation using the spliced contract and returns can be calculated correctly by using the backadjusted contract.

3.3.3. Merging process

The data used in this thesis is sourced from several exchanges which are located in different time zones around the world. Each trading record has a time stamp which refers to the local time of the exchange. As part of the merging process, all time stamps are converted into Australian Eastern Standard Time taking daylight saving time in each time zone into account.

All available datasources are merged together into one large dataset for this thesis. During the merging process, dates from different time zones are compared and aligned so that no look ahead bias is introduced into the simulation. This way only data is used that had been historically available at that time.

Figure 3.9 gives an overview of the contracts and corresponding market hours used in the thesis. The 5th of January is used as an example in the diagram to illustrate different time zones. The SPI200 trades almost 24 hours a day during day and night sessions. The market is only closed for short periods of time between the day and night sessions. The data used in this study contains information about both sessions. Figure 3.9 illustrates that the trading day of the 5th of January actually starts with the night session at 5:10pm of the previous day (4th of January) and ends at 4:30pm (5th of January). The times shown in figure 3.9 show Australian times and the corresponding US times in brackets. By converting the times into US times, daylight saving in Australia as well as the US has been taken into consideration. Since it is summer in US during the Australian winter and vice versa, the time difference between exchanges can vary by two hours. In this study, the worst case in regards to the time difference calculation is assumed which is the case when the difference between the time zones is the greatest.

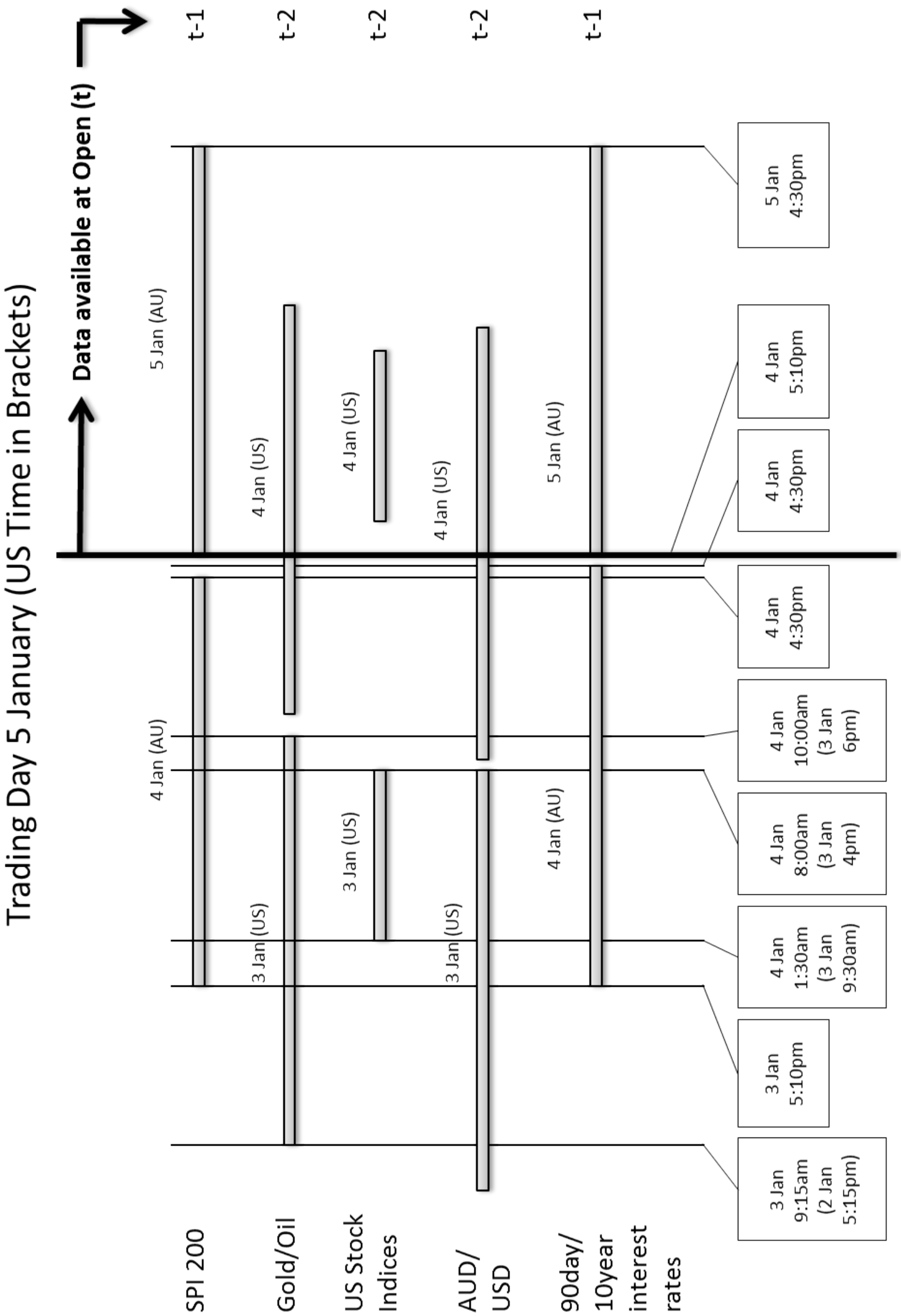

Figure 3.9.: Timing differences between data series

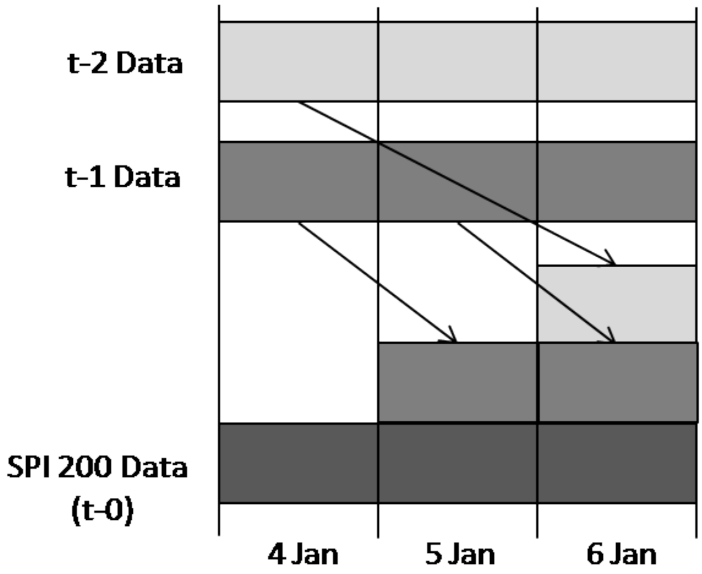

Figure 3.10.: Alignment of datasets

Figure 3.10 shows how the datasets are aligned. The datasets marked with t-1 are delayed by one day and the datasets marked with t-2 are delayed by two days. It is important to remember that for example the t-2 data is not two days old when used. In fact, the t-2 data might just become available a couple of hours before it is used. The difference in the timestamp is just due to the difference in time zones and the fact that trading sessions do not start at midnight.

3.3.4. Partitioning of data

In machine learning and optimization studies it is common to split the available data into two subsets. The first subset is used to train the machine learning technique while the second subset is used for performance evaluation. In the literature, there do not seem to be strict rules on how to split a dataset into two subsets.

For example, Majhi et al. (2008) use daily closing prices for the development of a new clonal particle swarm optimization technique. Out of the total number of 3228 samples, the authors use 2510 patterns for training and set aside the rest for testing purposes.

Huang & Wu (2008) use 70% of data points for training their support vector machine model in a batch manner and leave 30% for the evaluation of the prediction models.

Chu et al. (2009) use a five year period of stock index data for the simulation of a fuzzy dual-factor time-series model for stock index forecasting. The authors use two simulation approaches for the evaluation of the proposed model. The first approach uses the first three years for training and the remaining two years of data for evaluation purposes. The second approach is a moving window testing approach which goes through the dataset and uses one year for the training and six months for testing.

Depending on the amount of data available, some authors also decide to split the dataset into three subsets used for training, validation, and testing. For example, Leung et al. (2000) use data from 1967 to 1985 to estimate parameters for several forecasting techniques and then use data from the period of 1986 to 1990 for the validation of these parameters. Only if the parameters pass the validation test, the model is advanced to the out of sample period from 1991 to 1995.

Faria et al. (2009) use neural networks and adaptive exponential smoothing methods for the prediction of the Brazilian stock market and use a ratio of 90:10 which the authors describe as an acceptable relation between training and test set.

Abraham et al. (2001) use a ratio of 80:20 for the development of hybrid intelligent systems for stock market analysis.

The literature review reveals that there are only rough guidelines available to the split of the dataset into training and testing subsets. A common approach seems to be to select the training period wide enough to cover typical market behaviour. (Azoff 1994, Vanstone & Finnie 2009)

In this thesis a ratio of 50:50 is used. This means data from May 2000 to April 2005 is used for training the neural network and data from May 2005 to April 2010 is used for out-of-sample testing. The ratio of 50:50 has been chosen so that the out-of-sample period covers one bull market (2005-2006) and one bear market (2007-2010). Therefore, the performance of the neural network model can be investigated under different market characteristics.

3.3.5. Cross Hedging

The literature shows that hedging with stock index futures has been widely studied (Lee & Tsang 2010). Most of the reviewed articles use a stock index as a proxy for a diversified portfolio that is being hedged.

For example, Park & Switzer (1995) examine a GARCH based hedging method using the U.S. S&P 500 index futures and the Canadian Toronto 35 index futures. The authors use the corresponding spot market data in form of the S&P 500 index and the Toronto 35 index for the evaluation of the economic viability of their hedging method. Lafuente & Novales (2003) use the Spanish Ibex 35 index and corresponding futures data to analyse optimal hedge ratios. Alizadeh & Nomikos (2004) analyse the relationship between spot and futures prices in the FTSE 100 and S&P 500 markets using a Markov regime switching approach for hedging purposes. Lee & Yoder (2007) also uses stock index spot data to evaluate their regime-switching time-varying hedging model and Kenourgios et al. (2008) analyse the S&P 500 stock index to estimate hedge ratios and hedging effectiveness.

Using the stock index as a representation of a diversified portfolio is very common in the hedging literature. However, utilising only the stock index as portfolio representation for the assessment of hedging effectiveness leads to a somewhat biased result since the movement in the stock index and stock index futures are stronger correlated than movements in a real world portfolio and stock index futures.

Butterworth & Holmes (2001) analyse the hedging effectiveness of the UK FTSE-100 and FTSE-mid250 futures contracts. The authors criticise previous studies that use only portfolios which mirror index underlying futures contracts. Therefore, a spread of investment trust companies (ITCs)[1] is utilised. An ITC can be used as a proxy for a real world portfolio since an investment company holds a wide range of shares in its portfolio, which is managed by professional managers. The authors state that by analysing ITCs the hedging effectiveness for actual diversified portfolios can be assessed rather than artificially constructed portfolios for research purposes.

In this study, we follow the methodology of Kofman & McGlenchy (2005). The authors use sector indices in order to represent a more realistic share portfolio which is not perfectly correlated to stock index futures movements. Kofman & McGlenchy (2005) analyse dynamic index futures hedging on the Hong Kong exchange. In their study, the authors use the Hang Seng Index (HSI) and the Hang Seng Index Futures (HSIF) to represent a perfect hedge scenario. For a cross-hedge scenario the two sub-indices, the Hang Seng Commerce and Industry Index (HSCI), and the Hang Seng Finance Index (HSF) are used instead of the HSI.

In this study, the effectiveness of the proposed ANN based hedging technique is evaluated using the ASX 200 index representing a diversified portfolio of shares and the SPI 200 futures contract as hedging instrument. In addition, the data of 10 Australian sector indices is used to examine the hedging effectiveness between the sector index and the SPI 200 contract in a cross-hedging scenario. Table 3.4 gives an overview of the individual sector indices used in this study[2].

[1] In Australia an ITC is called a Listed Investment Company (LIC). According to the ASX website (ASX 2011*a*) "LICs provide exposure to a diversified portfolio of investments on behalf of their investors. [...] LICs are closed-end, meaning they do not regularly issue new shares or cancel shares as investors join and leave the fund. Instead, investors buy and sell to each other on ASX."

[2] Please refer to http://www.asx.com.au/products/indices/types/sector.htm for a full description of the sector indices.

Index	**Industry groups included**
S&P/ASX 200 Energy Index (XEJ)	Construction or provision of oil rigs, drilling equipment and other energy related service and equipment, including seismic data collection; companies engaged in the exploration, production, marketing, refining and transportation of oil and gas products, coal and other consumable fuels
S&P/ASX 200 Materials Index (XMJ)	Companies that manufacture chemicals, construction materials, glass, paper, forest products and related packaging products, and metals, minerals and mining companies, including producers of steel
S&P/ASX 200 Industrials Index (XNJ)	Manufacture and distribution of capital goods, including aerospace & defence, construction, engineering & building products, electrical equipment and industrial machinery; the provision of commercial services and supplies, including printing, employment, environmental and office services; the provision of transportation services, including airlines, couriers, marine, road & rail and transportation infrastructure
S&P/ASX 200 Consumer Discretionary Index (XDJ)	Automotive, household durable goods, textiles and apparel and leisure equipment; hotels, restaurants and other leisure facilities, media production and services, and consumer retailing and services.
S&P/ASX 200 Consumer Staples Index (XSJ)	Manufacturers and distributors of food, beverages and tobacco and producers of non-durable household goods and personal products; food & drug retailing companies; hypermarkets and consumer super centers
S&P/ASX 200 Health Care Index (XHJ)	Companies who manufacture health care equipment and supplies or provide health care related services; owners and operators of health care products, providers of basic healthcare services, and owners and operators of health care facilities and organisations

Table 3.4: List of Australian sector indices (Continued on next page)

Index	**Industry groups included**
S&P/ASX 200 Financial Index (XFJ)	Companies involved in activities such as banking, mortgage finance, consumer finance, specialised finance, investment banking and brokerage, asset management and custody, corporate lending, insurance, and financial investment, and real estate, including real estate investment trusts (REITs)
S&P/ASX 200 Information Technology Index (XIJ)	Companies that primarily develop software in various fields such as the internet, applications, systems, databases management and home entertainment, and companies that provide information technology consulting and services, as well as data processing and outsourced services; manufacturers and distributors of communications equipment, computers & peripherals, electronic equipment and related instruments; semiconductors & semiconductor equipment manufacturers
S&P/ASX 200 Telecommunications Services Index (XTJ)	Companies that provide communications services primarily through a fixed-line, cellular, wireless, high bandwidth or fiber optic cable network
S&P/ASX 200 Utilities Index (XUJ)	Electric, gas or water utilities, or companies that operate as independent producers or distributors of power

Table 3.4.: List of Australian sector indices

Since the sector indices are part of the S&P/ASX 200 index, movements in the sector indices are correlated to movements in the S&P/ASX 200 index, but the degree is varying. For example, the consumer discretionary index is more sensitive to economic cycles than the consumer staples index. (ASX 2011*b*)

Using sector indices gives us an indication of the cross-hedging performance of the proposed ANN based hedging strategies.

3.4. Hedging Strategies

The first ANN based hedging technique analyses the current state of the stock market. The ANN makes a prediction and indicates whether unfavourable market conditions are expected or not. If good conditions are expected, it is not necessary to hedge and therefore the portfolio of stocks is left unprotected. If, however, the market timing ANN predicts unfavourable market conditions, the portfolio needs to be protected by short selling stock index futures.

The second ANN based hedging technique also analyses the current state of the stock market. The difference from the first technique is that the portfolio is always protected by short selling stock index futures. Only the degree of protection varies according to the strength with which the ANN predicts a downturn in the stockmarket.

The ANN models are compared to the two naive strategies of never hedging and hedging every exposure. Two more advanced selective hedging models found in the foreign exchange literature are to hedge when the futures price is at a premium or to hedge when excessive volatility is observed in the market. (McCarthy 2003)

The hedge rule based on the futures price level stipulates to only hedge if the futures price is at a premium, which means that the futures price is higher than the underlying stock index. The strategy is also said to be based on the random walk hypothesis. The random walk hypotheses states that the current index level is the best estimate of future index prices and therefore that higher futures prices will return to the index level (Simpson & Dania 2006).

The hedging strategy based on volatility protects the portfolio when the volatility of the stock index is deemed to be excessive. McCarthy (2003) defines volatility to be excessive when the moving average of the short term volatility is greater than the moving average of the long term volatility. The short term volatility is expressed by the moving average of the previous 6 month volatility versus 12 month for the long term.

3.5. Hedge Ratio Estimation

The hedge ratio is used to calculate the number of futures contracts which need to be short sold in order to protect the portfolio against adverse price movements.

The minimum variance hedge ratio is calculated by performing a regression between the returns of the stock portfolio and the returns of the futures contracts. The hedge ratio is equivalent to the regression slope. According to Floros & Vougas (2004) hedge fund managers commonly use the ordinary least squares (OLS) regression to calculate futures hedge ratios. The hedge ratio is periodically recalculated as the correlation between portfolio and futures contract might change over time. Equation 3.3 shows how the hedge ratio is calculated. (Holmes 1996)

$$DS_t = a + bDF_t + E_t \tag{3.3}$$

DS_t = One month return of the share portfolio.
DF_t = One month return of the futures price.
a, b = Regression parameters, where b is the minimum variance hedge ratio h.
E_t = A residual term.

The hedge ratio h can then be used in equation 3.4 to calculate the number of futures contracts which need to be short sold in case a hedging decision is made. (Hull 2008)

$$N = h\frac{V_P}{V_F} \tag{3.4}$$

N = Number of futures contracts.
h = Hedge ratio.
V_P = Value of the portfolio of stocks.
V_F = Value of one futures contract.

3.6. Evaluation Metrics

In order to evaluate the performance of the proposed decision support system in relation to benchmark strategies, an evaluation metric is required. The following sections introduce metrics used for risk assessment in the financial literature. In addition, a test to evaluate the statistical significance of the simulation results is described.

3.6.1. Selective Hedging Performance

McCarthy (2003) states that one of the difficulties in making a statement regarding the effectiveness of hedging is that effectiveness has a different meaning to different hedgers. One group of hedgers might be willing to sacrifice a substantial part of the returns in order to have more certainty while for others a significant reduction in returns might not be acceptable.

Kofman & McGlenchy (2005) measure hedging performance in terms of the reductions in risk of the hedged portfolio relative to the unhedged portfolio. Yun (2006) uses mean and standard deviations of rate of return, Sharpe ratio, hedging effectiveness, and the expected utility based on mean and variance of returns as metrics to examine the hedging performance. Topaloglou et al. (2008) employ the conditional value-at-risk (CVaR) as a metric. The authors argue that CVaR is a coherent risk measure which is appropriate for asymmetric distributions. Furthermore, the geometric mean, standard deviation, Sharpe ratio, and the upside potential and downside risk are used. Kim et al. (2001) measure the forecasting performance of their models using the forecasting error in terms of mean squared error (MSE) and mean absolute deviation (MAD). The performance of the actual hedging strategy is benchmarked by calculating the reduction in variance of the unhedged return. The authors state that the greater the reduction in variance, the higher the degree of hedging effectiveness. Simpson (2004) compares selective hedging strategies by calculating the average return divided by the standard deviation of returns for each strategy. Simpson & Dania (2006) calculate the risk-return tradeoff for every strategy they examine. This is done by dividing the average return by the standard deviation of returns over the analysed period.

Selective hedging strategies are primarily found in the domain of foreign exchange hedging.

A standard measure of hedging effectiveness in this stream of literature is the minimum-variance model of Ederington (1979). The minimum-variance metric measures the reduction in risk (variance) of the hedged portfolio relative to the unhedged portfolio as shown in equation 3.5.

$$HE_{mv} = 1 - \frac{\sigma_p^2}{\sigma_s^2} \tag{3.5}$$

Where
HE_{mv} = Hedging effectiveness based on the minimum variance measure
σ_p^2 = Variance of the hedged portfolio returns
σ_s^2 = Variance of the spot (unhedged) portfolio returns

Ederington (1979) assumes hedgers to be indefinitely risk-averse and only be concerned with risk minimisation. This assumption is plausible in the foreign exchange market where producers might have exposures to currency fluctuations while producing abroad. These producers might want to minimise risk associated with currency fluctuation and are not primarily concerned with making a profit out of their hedging strategy. However, the assumption of being indefinitely risk-averse does not apply to the stock market. In the stock market, an indefinitely risk-averse investor would be better off, in terms of risk reduction, not to invest in the stock market at all. Therefore, the Ederington risk measure, as found in the foreign exchange literature, does not seem to be suitable for stock market hedging strategies.

A second measure frequently found in the literature is the Sharpe ratio based hedging effectiveness measure, developed by Howard & D'Antonio (Howard & D'Antonio 1984, Howard & D'Antonio 1987). The Sharpe Ratio is defined as the ratio of excess return per unit of risk. This ratio is a standard measure in the investment literature to compare hedging strategies. (Brailsford et al. 2001, Chen, Lee & Shrestha 2001, Howard & D'Antonio 1984, Howard & D'Antonio 1987, McCarthy 2003)

The Sharpe Ratio is calculated as shown in equation 3.6.

$$SR = \frac{R_p - R_f}{\sigma_p} \tag{3.6}$$

Where
SR = Sharpe Ratio
R_p = Portfolio return
R_f = Risk free rate of return
σ_p = Portfolio standard deviation

The hedging effectiveness based on the Sharpe Ratio measures the improvement in the hedging performance of the hedged portfolio relative to the unhedged portfolio (De Jong et al. 1997, McCarthy 2003). The Sharpe based hedging effectiveness is calculated as shown in equation 3.7.

$$HE_{sr} = \frac{R_f + (\frac{R_p - R_f}{\sigma_p})\sigma_s - R_s}{\sigma_s} \tag{3.7}$$

Where
HE_{sr} = Hedging effectiveness based on Sharpe Ratio
R_f = Risk free rate of return
R_p = Rate of return for the hedged portfolio
R_s = Rate of return for the spot (unhedged) portfolio
σ_p = Standard deviation of the hedged portfolio returns
σ_s = Standard deviation of the spot (unhedged) portfolio returns

In this study, the Sharpe based hedging effectiveness is used as a measure for comparing selective hedging strategies. Similar to Vanstone (2006), only price movements due to portfolio and hedging returns are considered and therefore the hedging effectiveness calculation assumes a risk free rate of zero. Schwager (1996) argues that using a risk free rate of zero simplifies the calculation and does not alter the theoretical implications since the same risk free rate is used for all analysed strategies.

According to Schwager (1996), the Sharpe Ratio has some potential drawbacks which apply equally to the measure of hedging effectiveness:

- **No differentiation between upside and downside variation**
  The Sharpe Ratio only takes the standard deviation of returns into consideration and does not distinguish between upside and downside fluctuations. For example, if on average a portfolio of stock has very sharp upside swings and only low drawdowns, the Sharpe Ratio calculation penalises the deviations from the average even though the deviations are in the favour of the investor.

- **No differentiation between intermittent and consecutive losses**
  Since the Sharpe Ratio measures risk in terms of volatility, there is no differentiation in regards to intermittent and consecutive losses. For example, two portfolios

may have the same Sharpe Ratio and a standard deviation of 5%. The first portfolio may have a maximum drawdown of equity of 10% by having alternating periods of gains and losses. The second portfolio, which has the same Sharpe Ratio, may have a maximum drawdown of 20% by having consecutive losing periods.

In order to address these drawbacks, the additional metrics shown in table 3.5 are calculated to get a better understanding of the hedging performance. The table shows a description and short explanation of the benefits of each metric.

Metric	**Description**
Net Profit %	Total net profit expressed in percentage terms in relation to the initial capital.
Annualised Return %	The total percentage gain expressed as an annualised figure.
Maximum Drawdown %	The absolute maximum drawdown of the selective hedging strategy over the analysed period.

Table 3.5: List of performance metrics (Continued on next page)

Metric	Description
Sortino Ratio	The Sortino Ratio was developed by Frank A. Sortino. The Sortino Ratio addresses the shortcoming of the Sharpe Ratio that no differentiation between upside and downside variation is made. The Sortino Ratio is calculated similar to the Sharpe Ratio. The only difference is that instead of the standard deviation of all returns, only the deviation of negative asset returns is used. This has the advantage that upside deviation has no negative impact on the ratio. The Sortino Ratio is calculated as shown in equation 3.8. $$SR = \frac{R_p - R_f}{\sigma_{pn}} \quad (3.8)$$ Where SR = Sortino Ratio, R_p = Portfolio return, R_f = Risk free rate of return and σ_{pn} = Standard deviation of negative portfolio returns. Although the Sortino Ratio distinguishes between upside and downside volatility, it also does not distinguish between intermittent and consecutive losses.

Table 3.5: List of performance metrics (Continued on next page)

Metric	Description
MAR Ratio	MAR is an acronym for the Managed Account Reports newsletter which developed the MAR ratio. The MAR ratio is calculated by dividing the annualised return by the Maximum Drawdown percentage as shown in equation 3.9 (MAR 2011). $$MAR = \frac{R_p - R_f}{MDP} \quad (3.9)$$ Where MAR = MAR Ratio, R_p = Portfolio return, R_f = Risk free rate of return and MDP = Maximum drawdown percentage of the analysed period. The MAR ratio addresses the shortcoming of the Sharpe Ratio that there is no differentiation between intermittent and consecutive losses. Schwager (1996) argues that using a maximum drawdown as a measure for risk is consistent with the way a lot of traders actually perceive risk. The drawback of this approach is that the maximum drawdown is a one time event which by definition has no statistical significance.
Ulcer Index	The Ulcer Index measures the depth and duration of equity drawdowns. The Ulcer Index penalises large drawdown more than small percentage drops in price and is an indication of the severity of drawdowns. The Ulcer Index is a measure of risk and is defined as the square root of the sum of the squared drawdowns (Martin 2005). A smaller Ulcer Index is preferable since it indicates that a system has less volatility and that the system might be more easy to tolerate in real-world trading.

Table 3.5: List of performance metrics (Continued on next page)

Metric	Description
Ulcer Performance Index	The Ulcer Performance Index is calculated similar to the Sharpe and MAR ratios, but uses the Ulcer Index as a risk measure (Martin 2005). $$UPI = \frac{R_p - R_f}{UI} \quad (3.10)$$ Where UPI = Ulcer Performance Index, R_p = Portfolio return, R_f = Risk free rate of return and UI = Ulcer Index. The calculation addresses both problems mentioned with the Sharpe Ratio. The Ulcer Performance Index only takes downward variation into account and penalises consecutive losses. Hedging strategies compared with the Ulcer Performance Index should cover the same time period as the calculation is sensitive to the timeframe used.

Table 3.5.: List of performance metrics

The discussion of performance metrics shows that every metric has particular drawbacks. In this study, the hedging effectiveness based on the Sharpe Ratio is used as primary performance measure since it is widely used and accepted by academics and practitioners. This makes the results of this study more easy to compare to other studies. The drawbacks of the measure discussed previously are addressed by the ratios mentioned in table 3.5 which will be used in conjunction with the hedging effectiveness measure.

3.6.2. Statistical Measures

The metrics mentioned before are the standard measures for performance evaluation found in the literature. Using a performance metric has the advantage that the performance is represented in a single number which can be used to compare investment strategies. In addition, statistical measures can be used to perform hypothesis testing and calculate confidence intervals in order to determine if the simulation results are statistically significant.

The seminal significance test developed by Jobson & Korkie (1981) and refined by Memmel (2003) for performing hypothesis testing based on the Sharpe ratio is widely used in the literature.

For example, DeMiguel et al. (2009) use the Memmel (2003) test to compare different diversification strategies and whether the Sharpe Ratios of two strategies are statistically distinguishable. Gasbarro et al. (2007) also uses the test to compare the performance of 18 country market indices.

Ledoit & Wolf (2008) argue that the test is not robust against time series characteristics like heavy tails and non independent and identically distributed returns which are quite common in financial data. As an alternative approach, the authors propose a studentised time series bootstrap for robust performance testing. The test is based on the circular block bootstrap method. Since its publication in 2008, the performance test of Ledoit & Wolf (2008) has become popular in the financial literature.

Walkshäusl & Lobe (2010) use the Ledoit & Wolf (2008) test in their study and find that the that the superior performance of global fundamentally weighted portfolios appears robust. Pätäri & Leivo (2009) analyse the performance of value strategies in the Finnish stock market and use the Ledoit & Wolf (2008) test to evaluate statistical significances of differences between Sharpe Ratios.

Kessler & Scherer (2010) examine momentum strategies across asset classes and use the Ledoit & Wolf (2008) test to evaluate if macro momentum provides a statistically significant increase in Sharpe Ratio over a pure equity investment. The authors argue that the non-normal nature of the return data does not allow them to employ the Jobson & Korkie (1981)/Memmel (2003) test. Instead, the authors use the bootstrapping technique by Ledoit & Wolf (2008). In particular, a block-wise bootstrapping with a block length of 3 month is used to capture autocorrelation. To test the null hypothesis the authors use a 95% confidence interval.

In this study, the performance test of Ledoit & Wolf (2008) is used to test the statistical difference of two hedging strategies using the null hypothesis of equality of the Sharpe Ratios.

3.6.3. Comparing Hedging Strategies

In order to evaluate the out-of-sample performance, the ANN based hedging strategies are compared to the benchmark strategies described in section 3.4. For the comparison, the hedging effectiveness based on the Sharpe Ratio is calculated. In addition, metrics that complement the Sharpe Ratio are calculated to get a full understanding of the behaviour of a hedging strategy. The Ledoit & Wolf (2008) test is then used to evaluate the robustness and statistical significance of the difference in hedging performance.

3.7. Automated Neural Network Training

In this study, the financial simulation software Wealth-Lab 6 from Fidelity Investments (Wealth-Lab 2011) is used to perform trading simulations over the study period. For data preprocessing and neural network training, Matlab from MathWorks (MathWorks 2011) is used.

Figure 3.11 illustrates how the data is exchanged between the two software packages. The data exchange bridge has been created as part of this study so that Wealth-Lab and Matlab are able to exchange information during a simulation run.

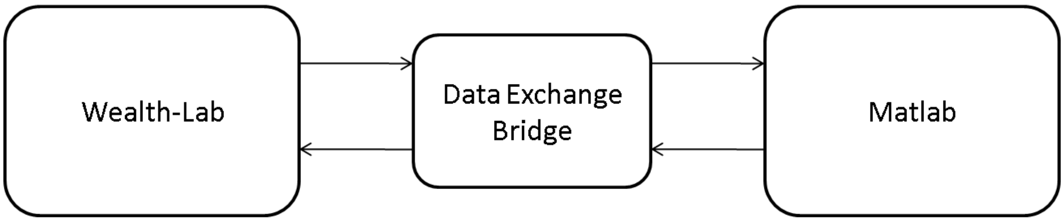

Figure 3.11.: Data exchange between Wealth-Lab and Matlab software packages

The following steps are performed to prepare and execute a simulation run:

Phase 1: ANN Training

- Import simulation training dataset into Wealth-Lab.
- Preprocess dataset for use with the ANN.
- Export ANN data to Matlab
- Create and train ANN in Matlab

Phase 2: Evaluation (in-sample and out-of-sample)

- Import simulation dataset into Wealth-Lab.
- Preprocess dataset for use with the ANN
- Export ANN data to Matlab
- Use previously trained ANN in Matlab and export result to Wealth-Lab

- Perform simulation in Wealth-Lab based on ANN forecast made in Matlab

Based on the in-sample performance of the trained ANN, it may be necessary to adjust training parameters of the ANN (see section 3.7.3 for details) and repeat the training executed in phase 1 until an optimal in-sample performance is reached.

Figure 3.12 illustrates that the data exchange bridge is implemented as plugin using the Wealth-Lab plugin architecture. This plugin contains the majority of the logic for the automated neural network training.

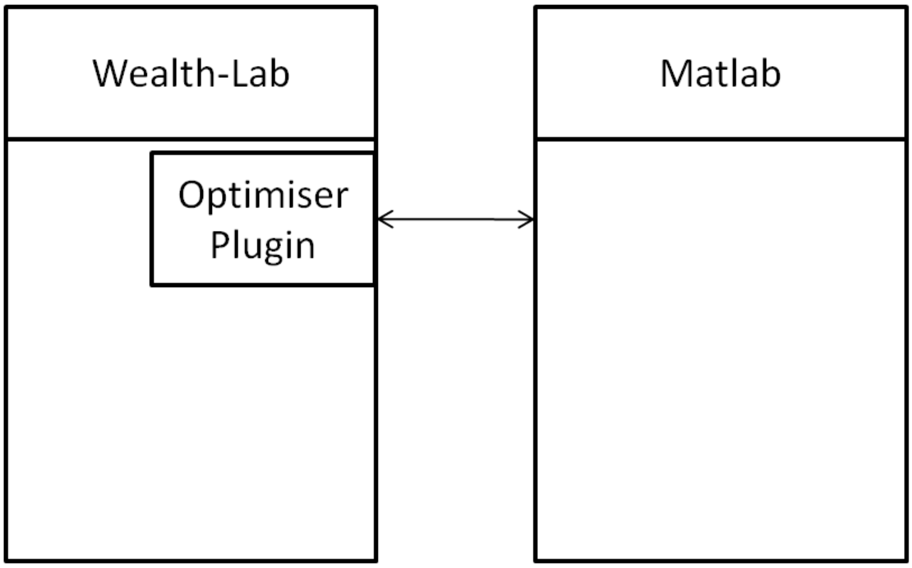

Figure 3.12.: Wealth-Lab Plugin Architecture

The plugin initialises the ANN training process in Matlab. After one training iteration, the ANN performance is evaluated on in-sample data in a simulation run in Wealth-Lab. Then the ANN is trained further in Matlab. This process is repeated until there is no improvement in the simulation performance for a predefined number of iterations. A contribution of this thesis is the proposal of an early stopping algorithm which uses a financial metric (e.g. Sharpe Ratio) instead of a statistical metric (e.g. MSE) as early stopping criterion. As part of the data exchange bridge, the proposed early stopping algorithm has been implemented. The training algorithm is described in more detail in section 3.7.2.

The following sections describe the input selection, parameter estimation, and output selection for ANN configuration.

3.7.1. Inputs

It is common in the neural network literature to preprocess datasets for the use as inputs for ANNs.

Lam (2004) states that data processing is an important step when machine learning techniques are trained and that preprocessing can reduce noise and irregularities in datasets.

Jaruszewicz & Mandziuk (2004) predict the NIKKEI Index and preprocess ANN inputs using percentage changes and technical indicators. All inputs are normalised and scaled into the range (-1,1). Zorin & Borisov (2002) also normalize the training dataset to the range of (-1,1) when training a neural network model for the Riga stock exchange. Zhang et al. (2005) analyse the Shanghai Composite Index and normalise the input data to the range of (0.1,0.9).

Olson & Mossman (2003) predict the return of Canadian stocks using accounting ratios and calculate annual percentage changes in the accounting ratios as a preprocessing step.

Absolute input values are often not as meaningful as the comparison of a value to a reference point like a historical value.

Dourra & Siy (2002) use technical indicators, in particular the rate of change indicator (ROC), as input into a fuzzy logic system. The ROC indicator measures the percent change in price from one period to the next. Shen (2003) examines timing strategies for the stock market and found that comparing variables to their historical ranges proves to be more valuable in the analysis than the use of absolute values. In particular, the study focused on extremely low or high values compared to historical ranges. McNelis (2005) also transforms neural network inputs into annualised changes as part of the preprocessing of variables.

Based on the literature review, the list of variables as shown in table 3.6 has been selected for the use as input for the ANN training.

Input	**Description**
ASX/SPI 200 Futures	12 month percentage change in the ASX/SPI 200 futures price
ASX 200 Volatility	Volatility measured as ratio of the short term volatility (6 month historical volatility) to the long term volatility (12 month historical volatility)
S&P 500 Index	12 month percentage change in the S&P 500 Index
AUD/USD Exchange Rate	12 month percentage change in the AUD/USD Exchange Rate
Oil Price	12 month percentage change in the oil futures price
Gold Price	12 month percentage change in the gold futures price
Interest Rates	Difference between the short term interest rate (90 day bank bills) and the long term interest rate (10 year government bonds).

Table 3.6.: Overview of input variables used

3.7.2. Neural Network Architecture

There are no clear rules in the literature about the configuration of an artificial neural network in regards to the number of hidden layers and the number of hidden neurons within each layer.

Olson & Mossman (2003) use one hidden layer and determine the number of hidden neurons by adding the number of input neurons to the number of output neurons and divide the result by two. Abraham et al. (2003) use one hidden layer and consisting of 26 neurons. Chaturvedi & Chandra (2004) examine different network configurations in their study and conclude that a lesser number of hidden neurons produce better results for simple data but do not perform well on complex data series. Constantinou et al. (2006) use one hidden layer consisting of eight neurons. The authors state that there is no reliable method of specifying the number of hidden layers but that usually one hidden layer is enough to approximate any nonlinear function assuming an appropriate number of hidden neurons within the layer. Dong et al. (2003) also state that a neural network with a single layer is sufficient to approximate any function given a sufficiently large size.

Halliday (2004) uses one hidden layer with 3, 5 and 10 hidden neurons and find that an increase in hidden neurons leads to a minimisation of output variation. Thawornwong & Enke (2004) choose a single hidden layer since neural networks with one hidden layer have been used successfully in the literature before. In regards the number of hidden nodes, Thawornwong & Enke (2004) state that a network with too many neurons can produce a network that memorizes the data and lacks the ability to generalise and a network with too few neurons may not be able to learn patterns in the data correctly.

Doeksen et al. (2005) use a dynamic approach to determine the number of hidden neurons used in a network. The authors iterate through network configurations starting with 10 hidden neurons up to 50 hidden neurons and a step size of two. Eventually the network with the smallest in-sample training error is selected for out-of-sample testing.

Figure 3.13 illustrates the concept of an dynamic neural network training and evaluation cycle. The neural network parameters are adjusted and the network is retrained until a satisfying in-sample performance is reached.

In this study, the methodology described by Vanstone & Finnie (2009) is followed in order to determine the number of neurons in the hidden layer. The neural network is configured with one hidden layer and only a small number of hidden neurons. The initial number of hidden neurons is determined by taking the square root of the number of input variables. The network is trained until no new low in the training performance is

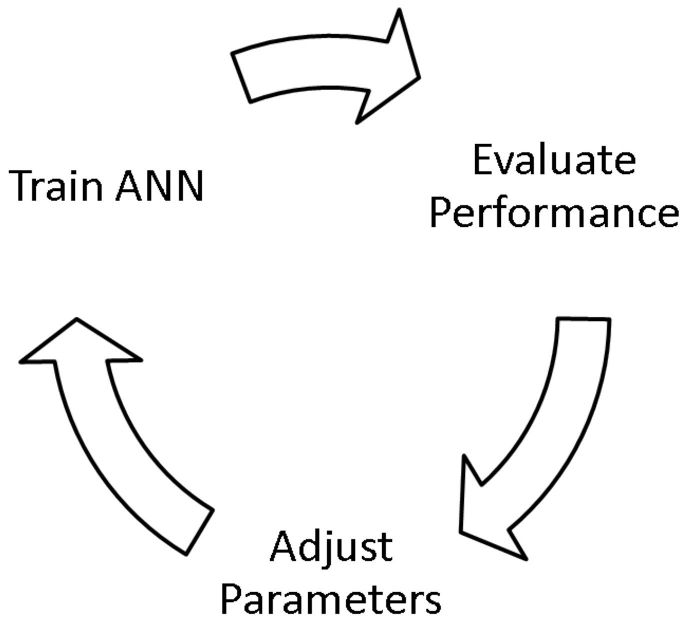

Figure 3.13.: Automated ANN training and evaluation cycle

reached for 2000 training epochs. Then the network is benchmarked using in-sample data. At this point a new neural network is created and the number of hidden neurons is increased by one. The training of the neural network with in-sample data is repeated and compared to the previous network using the in-sample metric. If the metric is superior to the metric of the previous network the process is repeated until an increase in the number of hidden neurons fails to further improve the in-sample metric. At this point, the neural network starts to overfit and a higher number of neurons leads to an inferior performance in regards to the performance metric.

Figure 3.14 visualises the training algorithm in form of a flow chart.

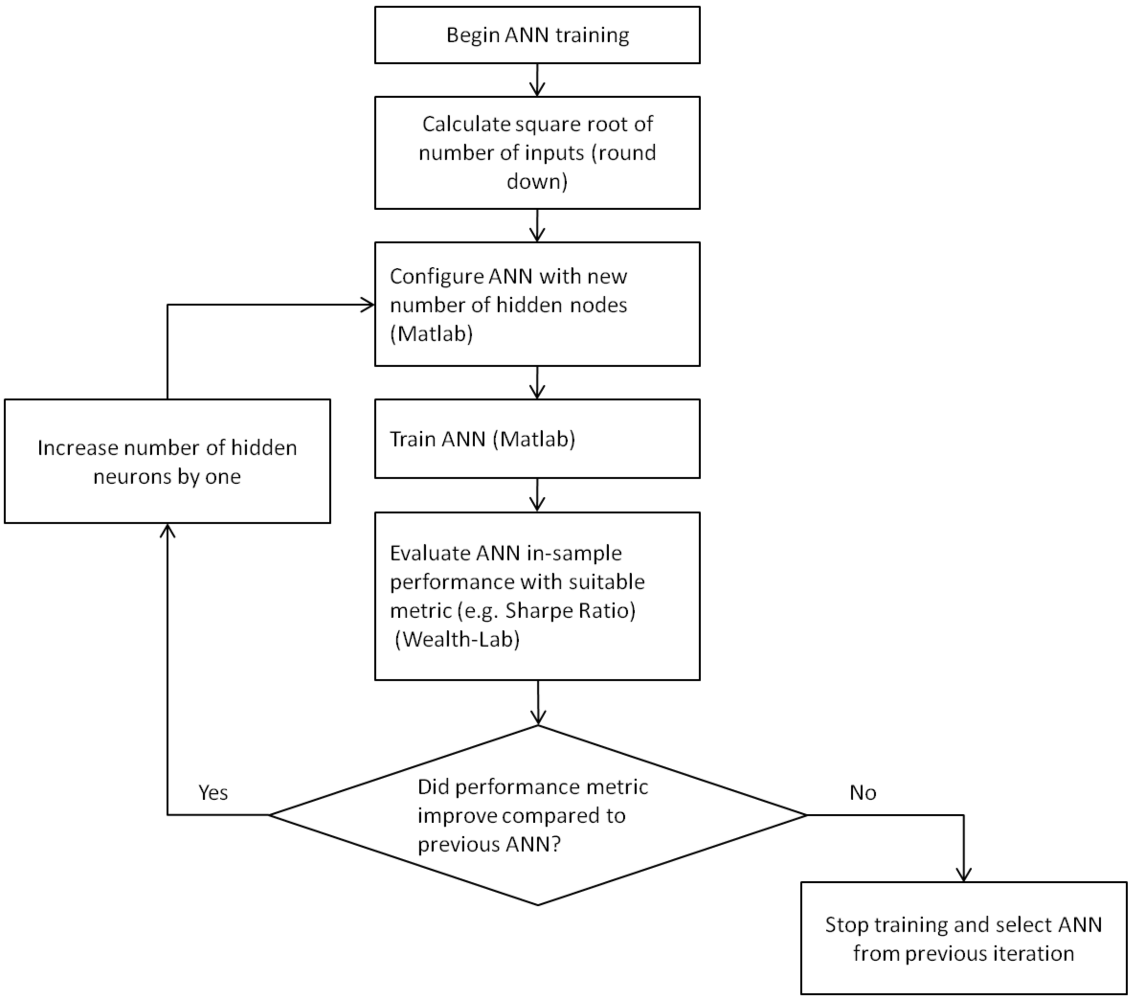

Figure 3.14.: Flow chart of automated ANN training algorithm

As mentioned before, the communication between Wealth-Lab and Matlab is performed through a data exchange bridge which has been created as part of this study.

Through the data exchange bridge it is possible to perform the neural network training shown in figure 3.14 in a fully automated manner. The advantage of the automated neural network training is that no human intervention is necessary which speeds up the training process. This can be very useful when the time-frame for ANN training is limited, e.g. if the ANN needs to be retrained between the close of the stock market and the opening on the next day.

The idea of a self configuring neural network is not new. However, previous studies use statistical metrics like MSE for the performance evaluation. White (1988) uses ANNs to optimise profit using IBM daily share prices and notes that minimising the ANN training error does not necessarily lead to an increased profit. Part of the contribution of this thesis is to address the mismatch in training objectives by creating an infrastructure which enables an automated neural network configuration based on a trading metric like the Sharpe Ratio.

Using a trading metric for the neural network evaluation is a variation of the early stopping training technique described by Prechelt (1998). For example, a neural network with 5 hidden neurons might have a lower MSE during neural network training than a network with 4 hidden neurons. If the network with 4 hidden neurons has a better trading metric (e.g. Sharpe Ratio) during in-sample testing than the network with 5 hidden neurons, the training process is stopped since the network begins to overoptimise.

3.7.3. Training method

The most commonly used neural network training methods in the financial forecasting literature are the error backpropagation (BP) and the Levenberg-Marquadt algorithm (LMA).

Armano et al. (2005) use the BP algorithm in combination with genetic algorithms to forecast the COMIT and S&P 500 indices and report a good forecasting capability which outperforms the buy & hold strategy. Chaturvedi & Chandra (2004) uses a standard back propagation network to predict stock prices for companies listed on the New York stock exchange. Halliday (2004) combines backpropagation ANNs with self organising maps (SOMs) to predict trends in equity markets and finds that the best performing network proves to be the one without a SOM layer. Situngkir & Surya (2004) analyse data in the Indonesian stock exchange and also report satisfying results using the back propagation training algorithm.

In addition to the BP algorithm, the Levenberg-Marquardt ANN training algorithm is frequently found in the literature. Originally, the LMA was developed by Levenberg (1944) and then later refined by Marquardt (1963). Hagan & Menhaj (1994) were the first authors who used the algorithm for neural network training and reported 10 to 100 times faster training cycles compared to standard gradient descent backpropagation.

Abraham et al. (2003) use the LMA for neural network training to forecast the Nasdaq 100 and NIFTY indices and find that their model provides a robust and reliable forecast. Safer & Wilamowski (1999) use the LMA to predict abnormal returns in quarterly earnings and argue that the Levenberg-Marquardt algorithm became popular because it usually converges in 5 to 10 iteration steps. Baek & Cho (2002) use the LMA in Matlab to minimise the sum of square error function in order to implement a up-trend detection for the KOSPI 200 futures. Bautista (2001) also use the LMA to predict the Philippine stock price index. The author states that the network is well trained which is reflected by an exponential decline in the training error. Koulouriotis et al. (2005) use the LMA among other techniques to perform short-term price predictions.

The Matlab Neural Network documentation states the following about the Levenberg-Marquardt algorithm:

”This algorithm appears to be the fastest method for training moderate-sized feedforward neural networks (up to several hundred weights). It also has an efficient implementation in MATLAB software, because the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB environment." (Demuth et al. 2008, p. 5-32)

The Matlab Neural Network Toolbox is used in this study and the Levenberg-Marquardt training algorithm is chosen because of the efficient implementation in Matlab.

3.7.4. Outputs

The majority of the reviewed literature uses one neuron in the output layer. The one output represents the value to predict. In ANN based forecasting, the choice of one output seems to be reasonable since using one output avoids the problem of having to choose between multiple conflicting forecasts.

Similar to the preprocessing described in section 3.7.1, it is common to normalize the value that should be predicted in order to achieve better forecasting results.

Dourra & Siy (2002) analyse investments in the stock market with a fuzzy system and processes outputs so that the value falls into a range between 0 and 100, 0 indicating a good selling opportunity a 100 and good buying opportunity. The closeness to a particular value represents the confidence in taking the corresponding action.

In this study the objective of the neural network training is to forecast drawdowns in the stock market up to one month ahead. Based on the literature the Rate of Change (ROC), Maximum Adverse Excursion (MAE), and the volatility are used as possible target variables for the ANN training. As part of this thesis, it was evaluated which of the three variables is most suitable for the proposed decision support system.

- **Rate of Change (ROC)**
  Gately (1996) compares different techniques to forecast stock indices with neural networks. The same neural network is used to forecast actual price changes in the S&P 500 index and a percentage change. The author concludes that forecasting the rate of change rather than an absolute price leads to a significantly improved

prediction accuracy.

The Rate of Change is calculated as follows:

$$ROC = 100 * \frac{Price_{period+1} - Price_{period}}{Price_{period}} \tag{3.11}$$

- **Maximum Adverse Excursion (MAE)**

  The MAE represents the largest loss over a given period of time. The MAE was developed by Sweeney (1996) and is used in risk management and the development of trading systems.

  The MAE is calculated as shown in equation 3.12.

$$MAE = \frac{OpenPrice_{period} - LowestPrice_{period}}{OpenPrice_{period}} \tag{3.12}$$

- **Volatility**

  Kotze (2005) defines volatility as a price series or an economic indicator that changes a lot and swings wildly. In the financial literature, the volatility is commonly analysed as a measure for price variation and it is used to quantify the risk of an financial instrument. The volatility is calculated by the standard deviation of the asset prices.

3.8. Limitations

3.8.1. Stock Indices

This study uses stock indices as proxies for diversified portfolios. In particular, the S&P/ASX 200 index is used as a proxy for a well diversified portfolio and the S&P/ASX 200 sector indices are used for the evaluation of cross hedging performance. Although this study accounts for trading costs and slippage, it does not account for rebalancing costs that would occur if these portfolios were actually traded on the stock exchange.

Rebalancing costs occur when stocks are added or deleted from the stock index. Accounting for rebalancing costs would require information about the historical composition of each stock index and would add a significant level of complexity. Therefore rebalancing costs have been defined as outside the scope of this thesis.

This limitation affects both the proposed ANN based strategies and the benchmark strategies.

3.8.2. Neural Networks

According to Hastie et al. (2009) ANNs are an excellent learning tool in terms of the ability to extract linear combinations of features and in terms of the predictive power. A major drawback of ANNs is the limited interpretability. Therefore, ANNs are often described as ”Black Box”. In contrast, decision trees are more interpretable, but lack the same predictive power as ANNs. This study uses ANNs because the literature review has shown that ANNs and ANNs combined with other learning techniques have proven to be a suitable forecasting tool in the financial literature.

In financial forecasting it would be beneficial to be able to examine the decision process in more detail so that investors can gain a greater confidence in the decisions made. There is a variety of literature which attempts to extract rules from neural networks and create if-then-else rules which then can be examined, see for example Mitsdorffer et al. (2002). However, this lies outside the scope of this study.

3.9. Extension of the Vanstone & Finnie (2009) Methodology

The methodology described by Vanstone (2006) and Vanstone & Finnie (2009) explains how to create and benchmark ANN based stock trading strategies. The methodology provides a practical guideline for researchers in the resource intensive process of neural network training for financial applications.

Part of the contribution of this thesis is the extension of the methodology of Vanstone & Finnie (2009) by automating the ANN training process and applying the methodology to the application area of financial hedging.

The benefit of the automated neural network training is that no human intervention is necessary which speeds up the training process. The uniqueness of the proposed algorithm lies in the fact that it is able to automatically determine a suitable ANN structure based on a financial trading metric like the Sharpe Ratio.

For the hedging of stock portfolios, stock index futures are used. As discussed in the literature review, futures differ significantly from stocks since futures data is not continuous but consists of individual contracts. In this thesis previous work is extended by describing how to train neural networks using non-continuous financial data.

In addition, the aim of hedging strategies is different from the aim of pure stock trading strategies so that different benchmark metrics and statistical tests are necessary. In this thesis parts of the methodology of Vanstone & Finnie (2009) are used and referenced. As described above, other parts of the methodology are not applicable to area of stock index hedging. The extension of the methodology of Vanstone & Finnie (2009) consists of addressing the described incompatibilities and developing a methodology for creating and benchmarking ANN based hedging strategies.

3.10. Testable Hypotheses

As discussed before, this thesis takes the concept of selective hedging found in the foreign exchange literature and applies it to the Australian stockmarket. A part of the contribution of this study is the extension of the methodology of Vanstone & Finnie (2009) to include the creation and benchmarking of ANN based risk management and hedging strategies.

The main goal of this thesis is to evaluate if artificial neural networks are a suitable decision support tool which can be used to create 'better' hedging strategies. The term 'better' means an improved hedging effectiveness compared to benchmark strategies as defined in section 3.6.

As part of this study the following hypotheses are evaluated:

- **Hypothesis 1**
  Selective hedging strategies based on artificial neural networks that use a binary hedging method can improve the hedging effectiveness in relation to conventional hedging strategies.

  The term binary hedging means in this context that a portfolio of shares is either fully protected or fully unprotected.

- **Hypothesis 2**
  Selective hedging strategies based on artificial neural networks that use a continuous hedging method can improve the hedging effectiveness in relation to conventional hedging strategies.

  Continuous hedging means that the portfolio is always hedged, but the degree of hedging varies according to the strength of the ANN output signal.

Together these two hypotheses can be used to answer the research question:
"Can artificial neural networks be used to improve the effectiveness of dynamic hedging strategies in the Australian stockmarket?"

4. Results and Analysis

This chapter presents the results of this thesis. The methodology is applied by creating the proposed decision support system and performing a simulation study on out-of-sample data. An analysis of data is performed and the results are presented. The key metrics discussed in the methodology chapter are calculated and a comparison to alternative risk management strategies is made.

4.1. Introduction

In order to create the proposed decision support system it was important to determine the ANN architecture which represents the heart of the system.

As part of the architecture selection, it was evaluated which ANN output signal performs best against in-sample data for dynamic hedging purposes. The methodology section describes three possible candidates for the ANN output:

- Rate of Change
- Maximum Adverse Excursion
- Volatility

In terms of ANN inputs, it may also be beneficial to consider if the ANN input signal is increasing or decreasing in relation to the previous ANN input. (Vanstone 2006)

Therefore, it was tested if using the change in the input signal as an additional input parameter improves the ANN performance.

After determining the optimal ANN configuration, the following two ANN based hedging strategies were created as part of this thesis:

- Binary ANN based hedging approach (ANN-Bin)
- Continuous ANN based hedging approach (ANN-Cont)

For the binary hedging approach, a threshold of the ANN output signal needs to be determined. If the ANN output falls below the threshold, the binary approach establishes a hedging position. Otherwise, the portfolio is left unhedged. For the continuous hedging approach, the percentage of the portfolio which needs to be hedged is determined in an ANN postprocessing step. This additional step is necessary, since the ANN output signal is not equally distributed across the output range. This postprocessing step is explained in section 4.5.2.

Both strategies were then evaluated using S&P/ASX 200 data representing a well diversified portfolio of shares, and sector indices representing portfolios less correlated to the SPI 200 futures.

For each of the hedging strategies the out-of-sample simulation results are shown and a discussion of evaluation metrics is provided. A detailed discussion of the evaluation metrics is only provided for the first hedging strategy to avoid repetitions across the simulations runs. The interpretation of evaluation metrics is independent of the actual hedging simulation. A summary of the metrics will be provided for all other simulations.

4.2. ANN Training

As described in the methodology section, it was evaluated whether the Rate of Change, Maximum Adverse Excursion or Volatility perform best as target for the ANN training. In addition, it was evaluated if considering the change in an ANN input parameter, i.e. considering if the input is increasing or decreasing in value, as additional parameter can improve the overall ANN performance. The ANN inputs consists of 7 data series including ASX/SPI 200 futures, ASX 200 volatility, S&P 500 index, AUD/USD exchange rate, oil price, gold price, and interest rates. Considering the change in each of the 7 inputs creates 7 additional inputs resulting in 14 inputs altogether.

The described combination of input and output values lead to the following 6 ANN combinations being trained using in-sample data from May 2000 to April 2005.

- ANN - Rate of Change: 7 Inputs
- ANN - Maximum Adverse Excursion: 7 Inputs
- ANN - Volatility: 7 Inputs
- ANN - Rate of Change: 14 Inputs
- ANN - Maximum Adverse Excursion: 14 Inputs
- ANN - Volatility: 14 Inputs

Each ANN was trained using the algorithm described in the methodology section. The initial number of hidden neurons was determined by taking the square root of the number of input variables. After one full training iteration, the network was benchmarked using in-sample data and the number of hidden neurons was increased by one. The process was repeated until an increase in the number of hidden neurons failed to further improve the in-sample metric.

The Sharpe Ratio and the hedging effectiveness measure were used to evaluate the in-sample hedging performance as described previously in section 3.6.1.

4.2.1. Rate of Change: 7 Inputs

The first analysed ANN used the 7 described data series as inputs and the one month forward Rate of Change (ROC) of the SPI 200 futures contract as target output. The Rate of Change is calculated as follows:

$$ROC = 100 * \frac{Price_{month+1} - Price_{month}}{Price_{month}} \tag{4.1}$$

Table 4.1 shows that the neural network training started with a network consisting of two hidden neurons.

Strategy (In-Sample)	Sharpe Ratio	Hedging Effectiveness
ANN - 2 Hidden Nodes	0.50	0.03
ANN - 3 Hidden Nodes	1.12	0.65
ANN - 4 Hidden Nodes	1.49	1.02
ANN - 5 Hidden Nodes	1.54	1.07
ANN - 6 Hidden Nodes	**1.62**	**1.15**
ANN - 7 Hidden Nodes	1.33	0.86

Table 4.1.: In-Sample Performance ANN - ROC 7 Inputs

The best in-sample performance is achieved with the ANN using 6 hidden neurons. Increasing the number of hidden neurons further leads to an inferior performance in terms of the Sharpe Ratio and Hedging Effectiveness. Figure 4.1 shows the correlation between actual output and target values of the best performing network configuration.

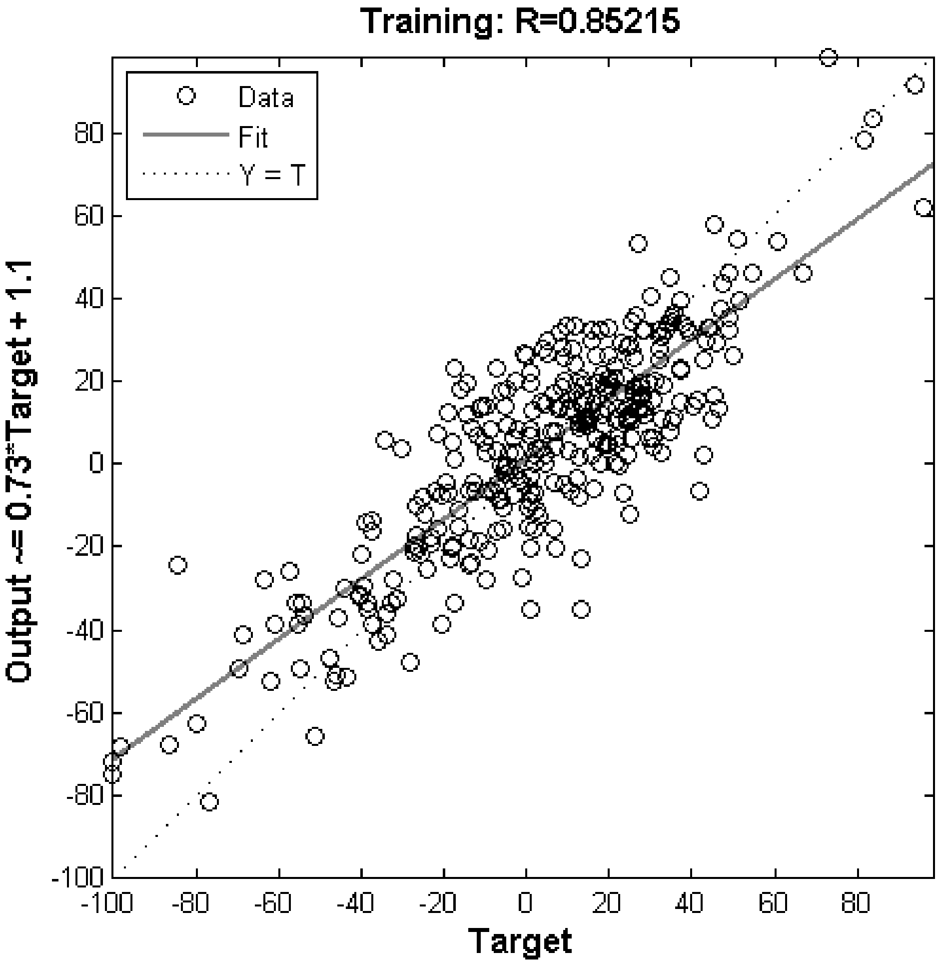

Figure 4.1.: Training Performance: ROC - 7 Inputs

4.2.2. Maximum Adverse Excursion: 7 Inputs

The next neural network uses 7 inputs and the Maximum Adverse Excursion (MAE) as output. The rationale for using the MAE is that the dynamic hedging approach focuses on preventing downward movements and the MAE only considers adverse price movements. The MAE is calculated as shown in equation 4.2.

$$MAE = \frac{OpenPrice_{Month} - LowestPrice_{Month}}{OpenPrice_{Month}} \tag{4.2}$$

Table 4.2 shows that the best performing configuration in terms of Sharpe Ratio and Hedging Effectiveness is the ANN with 5 hidden neurons.

Strategy (In-Sample)	**Sharpe Ratio**	**Hedging Effectiveness**
ANN - 2 Hidden Nodes	0.84	0.37
ANN - 3 Hidden Nodes	1.05	0.58
ANN - 4 Hidden Nodes	1.22	0.75
ANN - 5 Hidden Nodes	**1.43**	**0.96**
ANN - 6 Hidden Nodes	1.38	0.91

Table 4.2.: In-Sample Performance ANN - MAE 7 Inputs

Figure 4.2 illustrates a problem with using the MAE as output value for predicting stock market downturns. The output values are not spread across the output range, but the values are in particular clustered around zero. As a result, the overall network performance was not as good as the performance of the network using the Rate of Change as output in terms of Sharpe Ratio and Hedging Effectiveness.

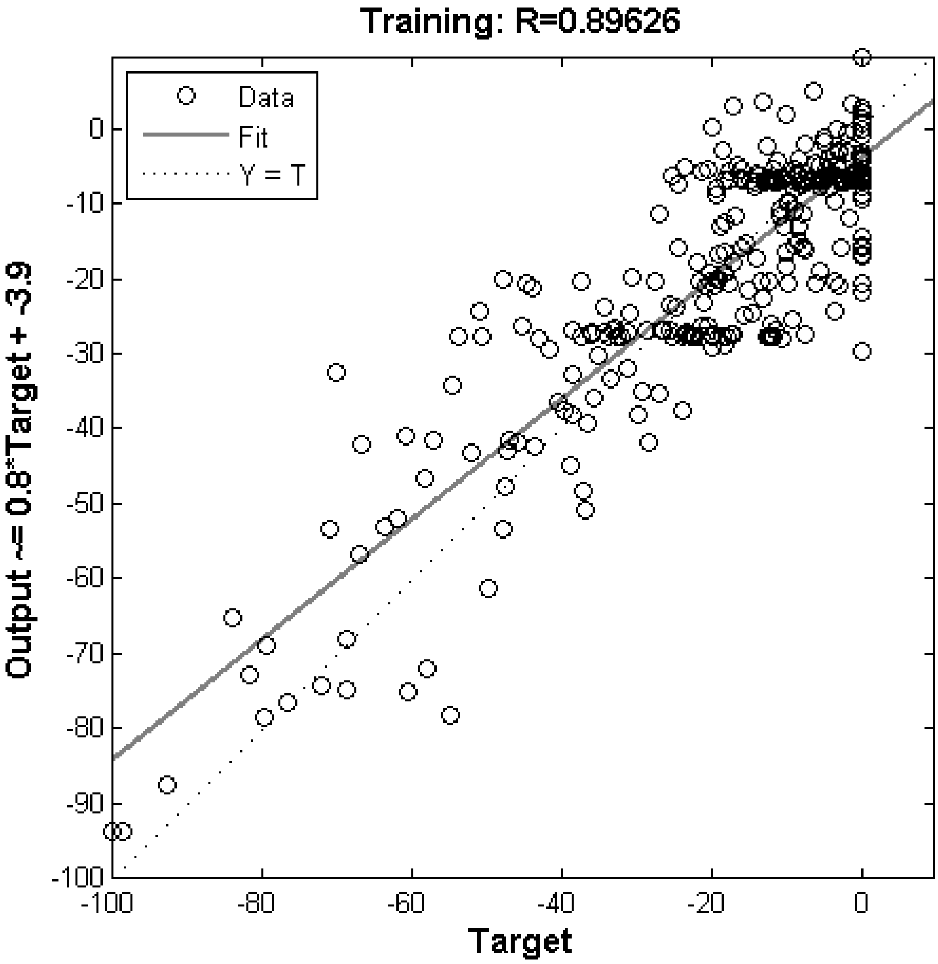

Figure 4.2.: Training Performance: MAE - 7 Inputs

4.2.3. Volatility: 7 Inputs

A third candidate for the ANN output is the volatility of the S&P/ASX 200 futures. Table 4.3 shows that the best performing network is the ANN configured with 3 hidden neurons.

Strategy (In-Sample)	**Sharpe Ratio**	**Hedging Effectiveness**
ANN - 2 Hidden Nodes	0.60	0.13
ANN - 3 Hidden Nodes	**0.75**	**0.28**
ANN - 4 Hidden Nodes	0.69	0.22

Table 4.3.: In-Sample Performance ANN - Volatility 7 Inputs

Figure 4.3 shows the relation between actual in-sample target outputs and the predicted ANN outputs. Compared to the ANNs trained using the Rate of Change and Maximum Adverse Excursion the ANN trained using the volatility performs worse in regards to the performance metrics.

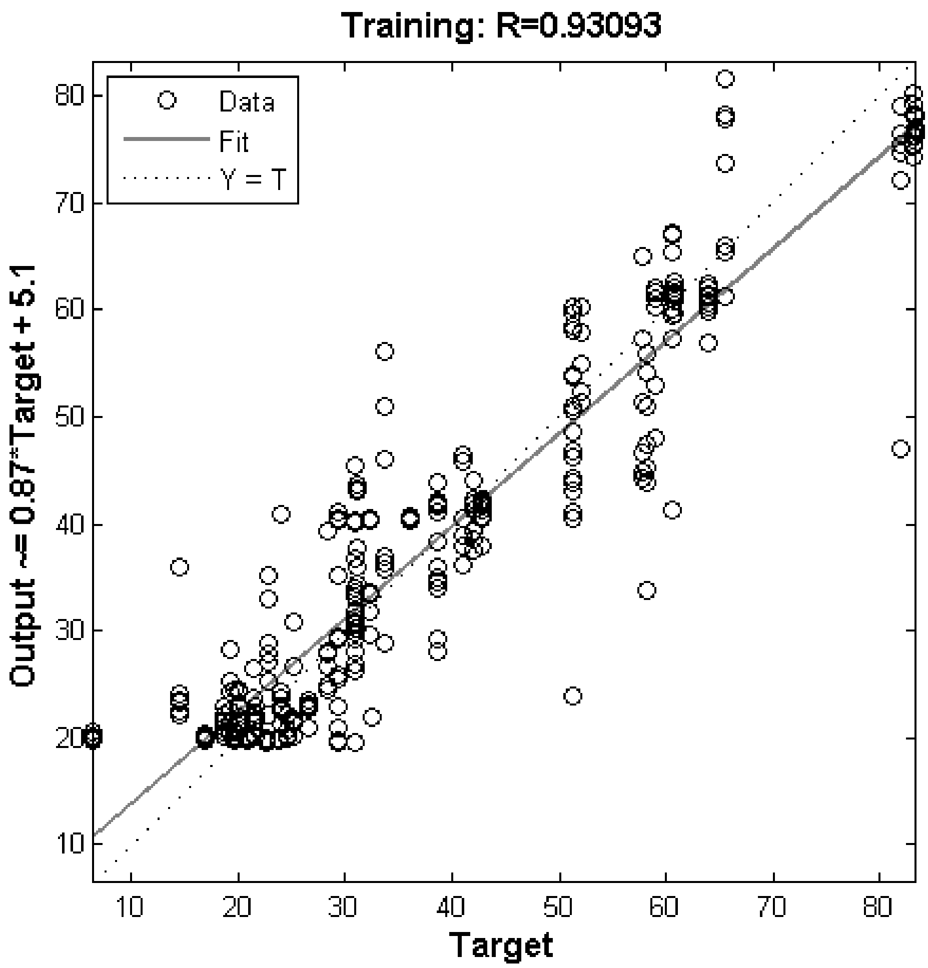

Figure 4.3.: Training Performance: Volatility - 7 Inputs

4.2.4. Rate of Change: 14 Inputs

The following three networks contain data from the ASX/SPI 200 futures, ASX 200 volatility, S&P 500 index, AUD/USD exchange rate, oil price, gold price, and interest rates as inputs. In addition, the change in each input parameter is added which led to 14 inputs altogether.

The change reflects if an input is increasing or decreasing in value and is calculated as shown in equation 4.3.

$$Change_{Input} = 100 * \frac{Input_{month} - Input_{month-1}}{Input_{month-1}} \tag{4.3}$$

Strategy (In-Sample)	Sharpe Ratio	Hedging Effectiveness
ANN - 3 Hidden Nodes	1.04	0.57
ANN - 4 Hidden Nodes	1.18	0.71
ANN - 5 Hidden Nodes	1.32	0.85
ANN - 6 Hidden Nodes	1.39	0.92
ANN - 7 Hidden Nodes	1.53	1.06
ANN - 8 Hidden Nodes	**1.70**	**1.23**
ANN - 9 Hidden Nodes	1.38	0.91

Table 4.4.: In-Sample Performance ANN - ROC 14 Inputs

Table 4.4 shows that the ANN configuration with 8 hidden neurons performs best during the in-sample training. Figure 4.4 illustrates the good training performance which also translates to an improved hedging performance compared to the ANN with only 7 inputs.

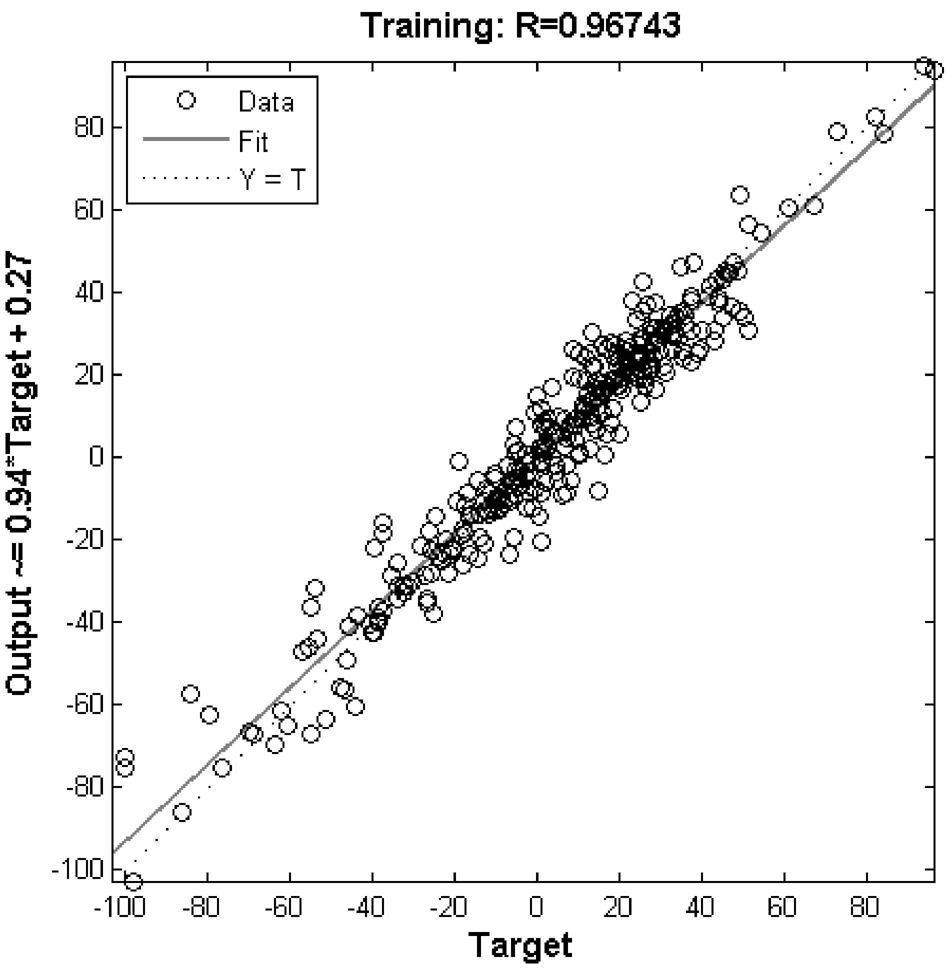

Figure 4.4.: Training Performance: ROC - 14 Inputs

4.2.5. Maximum Adverse Excursion: 14 Inputs

Table 4.5 shows the performance of ANN using 14 inputs and the Maximum Adverse Excursion as output. The best performing network is the ANN with 7 hidden nodes. In contrast to the Rate of Change output, the performance of the Maximum Adverse Excursion network did not improve in-sample by adding the change input variables.

Strategy (In-Sample)	**Sharpe Ratio**	**Hedging Effectiveness**
ANN - 3 Hidden Nodes	0.79	0.32
ANN - 4 Hidden Nodes	1.10	0.63
ANN - 5 Hidden Nodes	1.19	0.72
ANN - 6 Hidden Nodes	1.25	0.78
ANN - 7 Hidden Nodes	**1.37**	**0.90**
ANN - 8 Hidden Nodes	1.33	0.86

Table 4.5.: In-Sample Performance ANN - MAE 14 Inputs

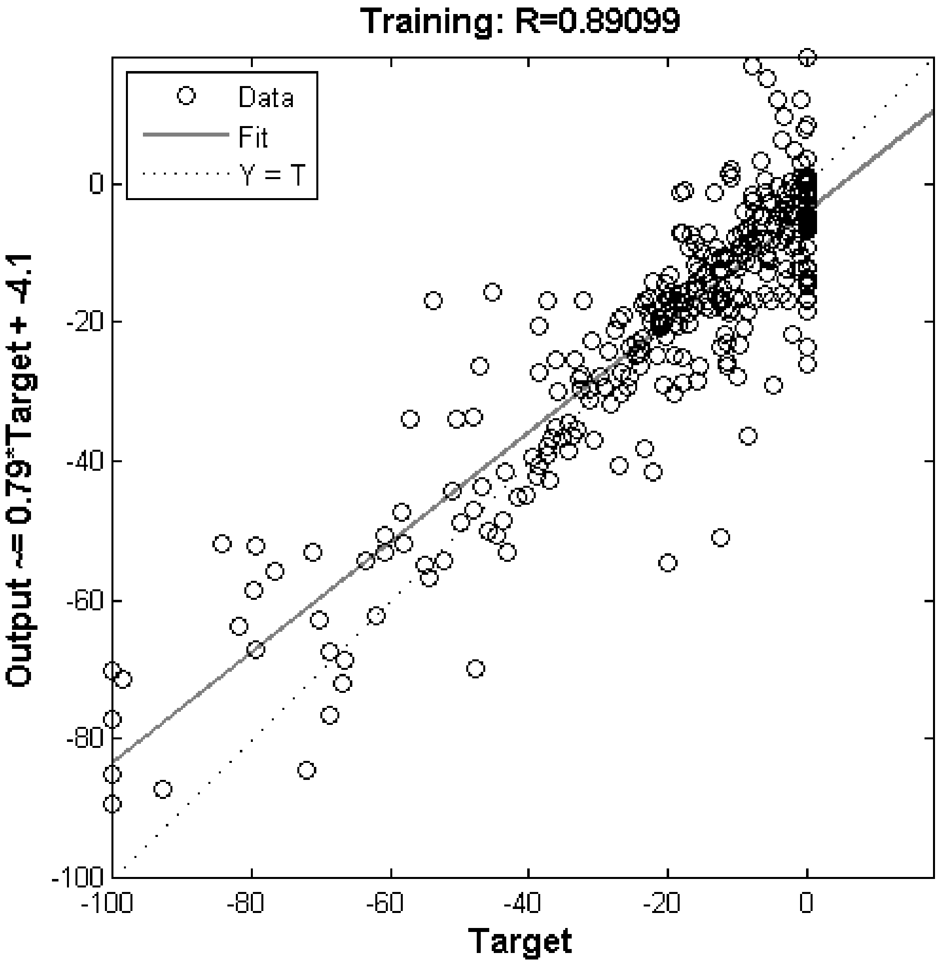

Figure 4.5.: Training Performance: MAE - 14 Inputs

4.2.6. Volatility: 14 Inputs

The last analysed network configuration was the ANN with 14 inputs and the SPI 200 volatility as output.

Strategy (In-Sample)	Sharpe Ratio	Hedging Effectiveness
ANN - 3 Hidden Nodes	0.21	-0.26
ANN - 4 Hidden Nodes	**0.46**	**-0.01**
ANN - 5 Hidden Nodes	0.10	-0.37

Table 4.6.: In-Sample Performance ANN - Volatility 14 Inputs

The best trained network was the network with 4 hidden nodes. The hedging effectiveness of the best performing network is negative which means that the networks fails to improve the risk-return trade-off compared to the unhedged portfolio. This means that this network was unsuitable for performing dynamic hedging decisions.

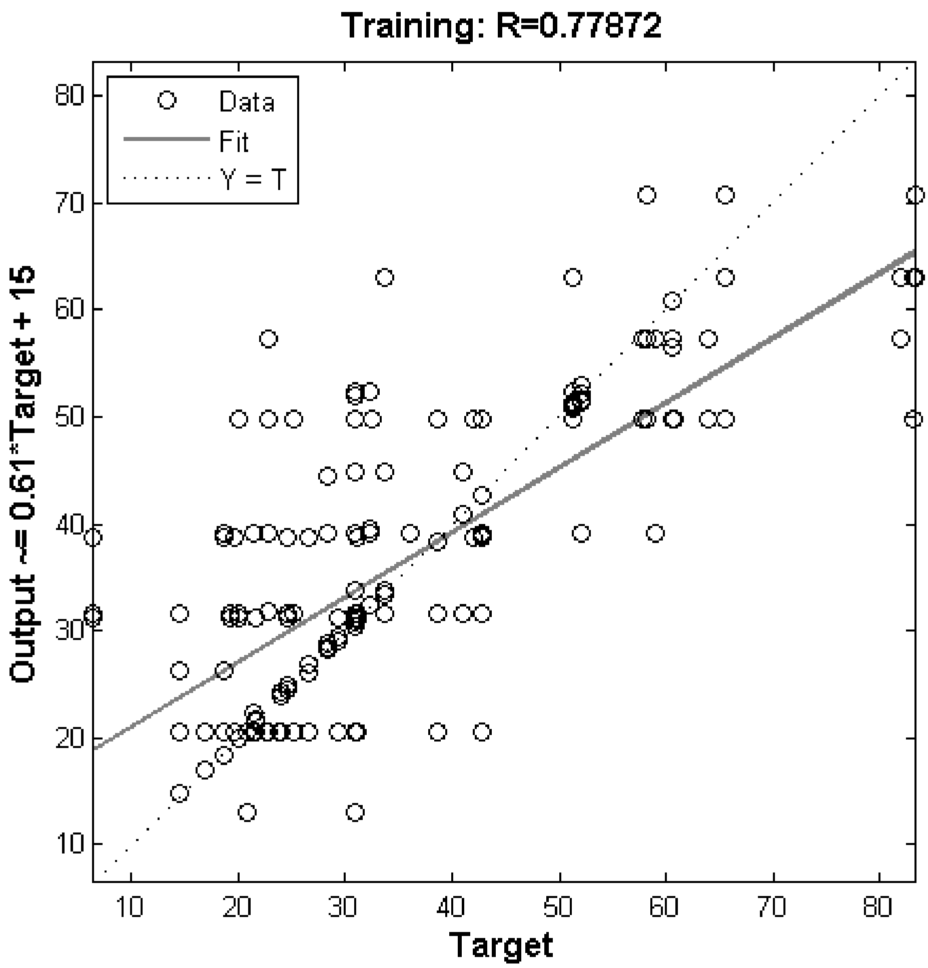

Figure 4.6.: Training Performance: Volatility - 14 Inputs

4.2.7. Selection of ANN architecture

Based on the in-sample analysis of the different network configurations the ANN with 14 inputs and the Rate of Change as output showed the best performance according to the in-sample metrics. During the training the ANN with eight hidden neurons achieved a Sharpe Ratio of 1.70 and a Hedging Effectiveness of 1.23 which was the best performance compared to the other network configurations. The information whether an input parameter is increasing or decreasing (direction) in value helped the network to increase the performance compared to the network lacking these inputs. Figure 4.7 illustrates the structure of the Artificial Neural Network which forms the base of the Decision Support System proposed in this thesis.

4.3. Simulation Portfolios

The S&P/ASX 200 index was used as a proxy for a well diversified portfolio and 10 sector indices were analysed as candidates for potential portfolios that are less correlated to the hedging instrument (SPI 200 futures) to simulate cross hedging. As mentioned in the literature review, there must be a strong correlation between the portfolio and the hedging instrument so that losses in the portfolio are offset by gains in the futures position. If there is no correlation between the portfolio and the index futures, entering an offsetting position in the futures contract does not have the desired effect of risk reduction. For each index the in-sample correlation of the SPI 200 futures returns to the index returns is calculated. The definition of strong correlation varies in the literature. In this thesis the following guideline given by Albert (2007) is used to interpret the degree of correlation.

- Correlation Coefficient >= 0.7: Strong Correlation
- Correlation Coefficient >= 0.3 and < 0.7: Moderate Correlation
- Correlation Coefficient < 0.3: Weak Correlation

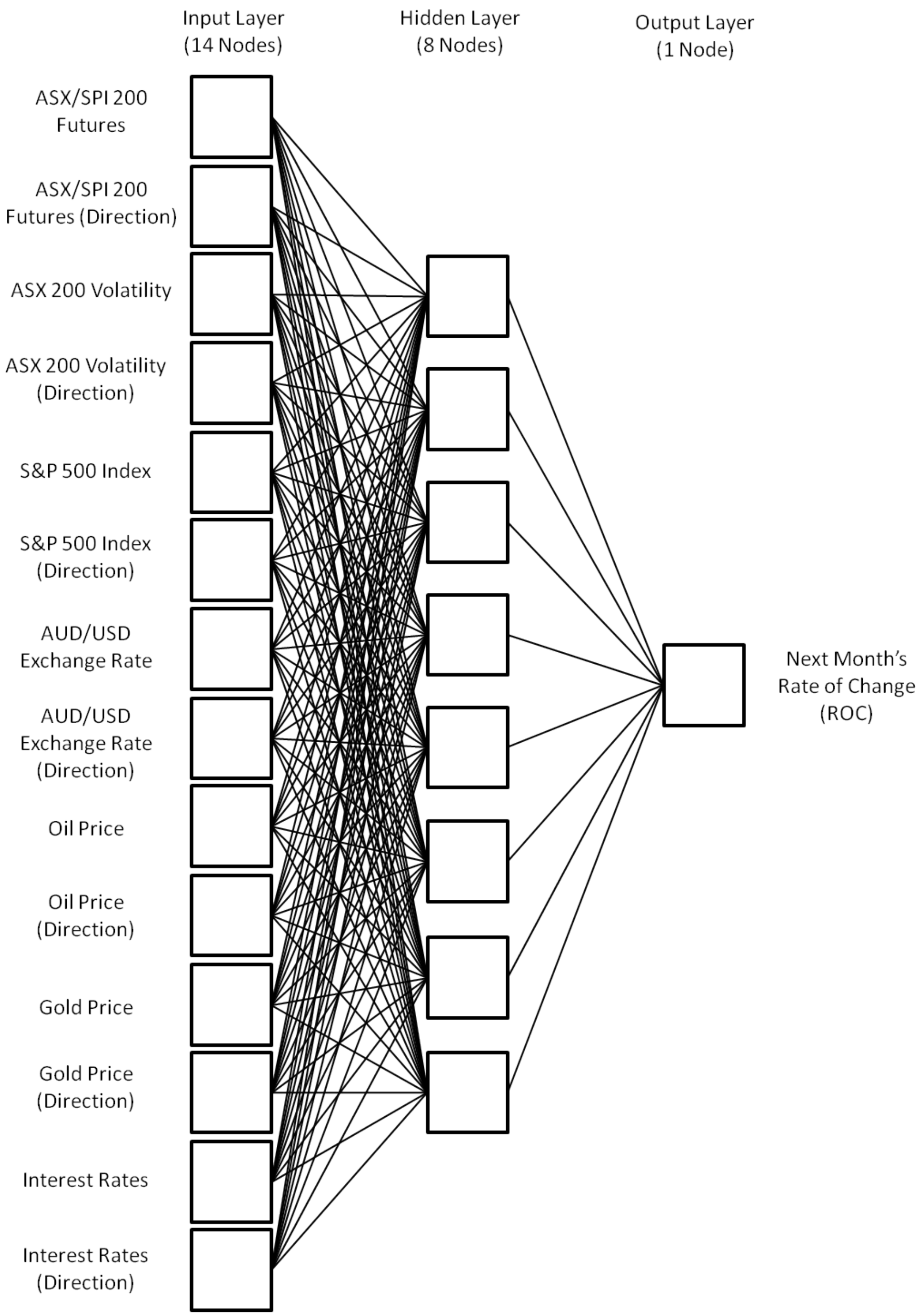

Figure 4.7.: Diagram of the best performing in-sample ANN

Table 4.7 shows each candidate portfolio represented by a (sector-) index.

Index	**Correlation Coefficient**
S&P/ASX 200	0.98
Energy	0.40
Materials	0.74
Industrials	0.70
Consumer Discretionary	0.73
Consumer Staples	0.44
Health Care	0.53
Financial	0.72
Information Technology	0.71
Telecommunications Services	0.20
Utilities	0.21

Table 4.7.: Correlation coefficients for (sub-)indices and index futures

The evaluation of correlation coefficients showed that the S&P/ASX 200 index shows the strongest correlation to the SPI 200 futures which was expected since the SPI 200 futures are based on the S&P/ASX 200 index. All other subindices show a weaker correlation. The energy, consumer staples, health care, telecommunications services, and utilities sector indices showed only a moderate to weak in-sample correlation to the SPI 200 index futures which means that the SPI 200 index futures are not a suitable hedging instrument. Hedgers wanting to hedge portfolios which have a strong exposure in these sectors need to look for a different hedging instrument. At the time of writing, there do not exist any futures on sector indices in Australia. In contrast, hedgers in the USA would have the option to choose between several sector index futures and then select the futures contract with the strongest correlation to their portfolio. Since an Australian hedger does not have this opportunity, the portfolios which do not show a strong correlation to the SPI 200 futures were excluded from this thesis. This represents the choice of a hedger not to choose the SPI 200 futures as a hedging instrument when she/he owns a portfolio which has only a moderate or weak correlation to the ASX/SPI 200 futures. This choice is independent of the proposed ANN based hedging framework and applies to all hedging strategies.

In terms of this thesis, the following list of indices was deemed suitable for hedging with ASX SPI 200 futures and was used for out-of-sample testing.

- S&P/ASX 200
- Materials
- Industrials
- Consumer Discretionary
- Financial
- Information Technology

4.4. Binary hedging approach

4.4.1. Introduction

In this section the binary hedging approach is evaluated using five years out-of-sample data beginning in May 2005 to April 2010. The objective is to evaluate the performance of the binary hedging strategy using Artificial Neural Networks. The binary ANN based hedging technique analyses the current state of the stock market and gives an indication whether unfavourable market conditions are expected or not. If good conditions are expected, it is not necessary to hedge and therefore the portfolio of stocks is left unprotected. If however the market timing ANN predicts unfavourable market conditions, the portfolio needs to be protected by short selling stock index futures. The term binary refers to the fact that there are only two states. The strategy is either fully hedged or fully unprotected.

4.4.2. Signal threshold

Table 4.8 lists the in-sample output range categorized into percentiles. For each output range the average monthly in-sample return is listed. The categorization into percentiles is used at a later stage for the continuous hedging approach and can be disregarded for the binary hedging approach. By inspecting table 4.8 the threshold of -4.88 is chosen for the binary hedging strategy since this is the ANN output strength threshold for which the expected return in greater than zero.

The binary ANN based hedging strategy consists of the following rule:

Hedge: Enter a hedging position if the ANN output value is smaller or equal to -4.88 to fully protect the portfolio.

Do not hedge: Leave the portfolio unprotected if the ANN output value is greater than -4.88 to allow for upside gain.

Output range (x)	Average monthly return (%)	# Obs
x <= -37.72	-5.93	82
-37.72 < x <= -21.67	-2.87	81
-21.67 < x <= -11.07	-1.53	82
-11.07 < x <= -4.88	-0.48	82
-4.88 < x <= 2.88	0.03	81
2.88 < x <= 11.17	0.71	82
11.17 < x <= 19.05	1.46	82
19.05 < x <= 24.26	2.32	81
24.26 < x <= 28.99	2.41	82
28.99 < x <= 36.75	3.44	82
36.75 < x	5.02	81

Table 4.8.: In-Sample ANN output vs. one month ahead return

4.4.3. Out-of-sample results S&P/ASX 200

Table 4.9 reports the out-of-sample hedging results for the S&P/ASX 200 index. The out-of-sample period uses data beginning in May 2005 to April 2010. The binary hedging strategy based on Artificial Neural Networks is called ANN-Bin. The performance is compared to the basic strategies of always hedging and leaving the portfolio unhedged. As explained in the methodology section, hedging strategies based on the futures premium and volatility are used in addition to the basic benchmark strategies for additional comparisons.

Metric	ANN-Bin	Unhedged	Always	Premium	Volatility
Net Profit	100.62%	17.45%	16.46%	50.52%	49.41%
Annualised Return	12.32%	2.72%	2.58%	7.06%	6.93%
Maximum Drawdown	-31.72%	-53.64%	-27.23%	-35.90%	-26.07%
Sharpe Ratio	1.20	0.26	0.42	0.70	0.74
Hedging Effectiveness	0.94	0.00	0.16	0.44	0.48
Sortino Ratio	1.12	0.36	0.51	0.58	0.85
MAR Ratio	0.39	0.05	0.09	0.20	0.27
Ulcer Index	7.70	21.76	10.19	11.53	8.29
Ulcer Perf. Index	1.60	0.13	0.25	0.61	0.84

Table 4.9.: Out-of-sample trading metrics: Binary hedging

Table 4.10 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio. The Ledoit & Wolf (2008) blockwise bootstrapping test with a block interval of 5 and 5000 bootstrap replications was used to test the null hypothesis H_0 that the difference of Sharpe ratios is zero. The alternative H_1 is that the difference is not zero. The Ledoit & Wolf (2008) test has been specifically designed for the purpose of comparing two Sharpe Ratios.

The hypothesis for the Ledoit & Wolf (2008) test is:

$H_0 : SR_{ANNBin} - SR_{Unhedged} = 0$
$H_1 : SR_{ANNBin} - SR_{Unhedged} \neq 0$

Metric	**ANN-Bin**	**Unhedged Portfolio**
Mean Monthly Return	1.01	0.31
Standard Deviation	2.92	4.05
Sharpe Ratio	1.20	0.26

Table 4.10.: Binary ANN hedging strategy return vs. unhedged portfolio return

The test statistic for the ANN-Bin hedging system allows the rejection of the null hypothesis at the 5% level and concludes that the Sharpe Ratio of the ANN-Bin hedging system is significantly different from the unhedged portfolio position. Specifically, test statistic = 3.83 , p = 0.0270 (< 0.05), two tailed.

4.4.4. Evaluation of Hedging Metrics

The binary ANN based hedging approach shows the best performance in terms of Sharpe Ratio and Hedging Effectiveness. As mentioned in the methodology section, each performance metric has it's strength and weaknesses so that it is beneficial to combine a number of metrics to get a better understanding of the overall out-of-sample performance. The following sections provide a brief discussion about each performance metric in the out-of-sample period.

4.4.4.1. Net Profit

The net profit of the ANN based hedging strategy lies at about 100% which means that the strategy was able to double the initial capital over the out-of-sample period of 5 years. The net profit of the ANN strategy is the highest of the analysed strategies. However, since the objective of the hedging strategy is not pure profit maximisation, the net profit figure needs to be evaluated in conjunction with other risk related metrics like the maximum drawdown or the Ulcer Index to be able to judge which kind of risk a hedger had to take in order to achieve the stated profit.

4.4.4.2. Annualised Return

The annualised return states the profit as an annualised figure. This makes it easier to compare strategies over different periods of time. The same guidelines in evaluating the net profit apply to the evaluation of this metric.

4.4.4.3. Maximum Drawdown

The maximum drawdown measures the largest percentage loss in equity over the analysed period of time. It also shows the impact the financial crisis had on portfolio returns. The maximum drawdown is a one time event and therefore does not carry any statistical significance. Nevertheless, investors take the maximum drawdown into account when evaluating investment strategies, since it gives an indication of the worst case performance. The ANN based hedging strategy was able to reduce the maximum equity drawdown from -53.64% (unhedged portfolio) to -31.72%. Generally a lower drawdown is preferable, however similar to the profit measures, the maximum drawdown should not be viewed in isolation. The objective of the ANN hedging strategy is to enhance the risk-adjusted return. A hedger with pure risk-minimisation in mind would have the option to invest in risk-free assets and not to invest into the stock market at all.

4.4.4.4. Sharpe Ratio

The Sharpe Ratio measures the return per unit of risk. The Sharpe Ratio is a standard performance measure in the financial literature. A higher Sharpe Ratio means a better performance in terms of risk-adjusted return. The ANN based hedging strategy was able to outperform the benchmark strategies in terms of the Sharpe Ratio.

4.4.4.5. Hedging Effectiveness

The Hedging Effectiveness measures the improvement in risk-adjusted return compared to the unhedged portfolio. A positive value indicates a better risk-adjusted performance and a negative value indicates a worse performance compared to the unhedged portfolio. Generally, higher values are desirable. The ANN based hedging strategies achieved the highest risk-adjusted return based on the unhedged portfolio.

4.4.4.6. Sortino Ratio

The Sortino Ratio is calculated similarly to the Sharpe Ratio but uses only downside variation as a measure for risk. Upside deviation has no effect on this ratio. A higher Sortino Ratio indicates a higher risk-adjusted return. From the Sortino Ratio point of view, the ANN based hedging strategy outperforms the other benchmark strategies.

4.4.4.7. MAR Ratio

The MAR ratio is calculated by dividing the annualised return by the maximum drawdown over the analysed period. Although the maximum drawdown is a one time event and therefore has no statistical significance, traders are interested in this measure since it gives an indication of worst case performance and this is how many traders perceive risk. The MAR ratio puts the annualised return in relation to the maximum drawdown risk measure. The ANN based hedging strategy has a higher annualised return and a lower drawdown compared to the unhedged strategy. Therefore, the MAR ratio is also better than the MAR ratio of the unhedged strategy. Also, the ANN based strategy performs best compared to the other benchmark strategies.

4.4.4.8. Ulcer Index

The Ulcer Index measures the depth and duration of equity drawdowns. The Ulcer Index penalises large drawdown more than small percentage drops in price and is an indication of the severity of drawdowns. A smaller Ulcer Index is preferable since it indicates that a system has less volatility and that the system might be easier to tolerate in real-world trading. As discussed before with other measures, the Ulcer Index should be viewed in conjunction with return based metrics (see Ulcer Performance Index).

4.4.4.9. Ulcer Performance Index

The Ulcer Performance Index measures the risk-adjusted return like the Sharpe Ratio, but uses the Ulcer Index as a measure for risk. Therefore, the Ulcer Performance Index takes the severity of drawdowns into account. The Ulcer Performance index suggests that the ANN based hedging strategy performed best in the out-of-sample simulation period.

4.4.5. Out-of-sample results cross hedging

The evaluation of the proposed binary ANN based hedging strategy showed that it had a good performance according to the analysed performance metrics and the S&P/ASX 200 portfolio. As discussed in section 4.3, the proposed machine learning technique will also be evaluated in terms of the following list of sector indices that fulfil minimum correlation requirements.

- Materials
- Industrials
- Consumer Discretionary
- Financial
- Information Technology

4.4.5.1. Materials Sector

Table 4.11 shows the out-of-sample results of the binary ANN based hedging strategy and the benchmark strategies applied to the materials sector. The out-of-sample simulation covers the period beginning in May 2005 to April 2010.

Metric	ANN-Bin	Unhedged	Always	Premium	Volatility
Net Profit	212.37%	70.86%	39.66%	132.03%	120.27%
Annualised Return	20.94%	9.35%	5.73%	15.09%	14.09%
Maximum Drawdown	-45.35%	-58.91%	-39.06%	-45.13%	-31.46%
Sharpe Ratio	1.23	0.53	0.41	0.92	0.90
Hedging Effectiveness	0.70	0.00	-0.12	0.39	0.37
Sortino Ratio	1.84	0.81	0.71	1.46	1.79
MAR Ratio	0.46	0.16	0.15	0.33	0.45
Ulcer Index	10.95	21.15	15.88	12.59	7.76
Ulcer Perf. Index	1.91	0.44	0.36	1.20	1.82

Table 4.11.: Out-of-sample cross hedging: materials sector

Table 4.12 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio.

The hypothesis for the Ledoit & Wolf (2008) test is:

$H_0 : SR_{ANNBin} - SR_{Unhedged} = 0$
$H_1 : SR_{ANNBin} - SR_{Unhedged} \neq 0$

Metric	**ANN-Bin**	**Unhedged Portfolio**
Mean Monthly Return	1.71	0.94
Standard Deviation	4.80	6.11
Sharpe Ratio	1.23	0.53

Table 4.12.: Statistics ANN-Bin vs. unhedged portfolio return: materials sector

The test statistic for the ANN-Bin hedging system allows the rejection of the null hypothesis at the 1% level and concludes that the Sharpe Ratio of the ANN-Bin hedging system is significantly different from the unhedged portfolio position. Specifically, test statistic = 4.318 , p = 0.0048 (< 0.01), two tailed.

The materials sector had a better performance compared with the S&P/ASX 200 index in terms of net profit over the analysed period. The materials sector resulted in a net profit of 70.86% whereas the market index achieved 17.45%. However, the materials sector had a maximum drawdown of -58.91% and the S&P/ASX 200 index had a drawdown of -53.64%.

The ANN-Bin strategy was able to reduce the maximum drawdown from -58.91% to -45.35% while achieving a net profit of 212.37% and annual return of 20.94%. Out of the analysed hedging strategies, the ANN-Bin strategy had the best risk-adjusted return over the out-of-sample period.

Overall, the ANN-Bin hedging strategy had an excellent performance in terms of risk-adjusted return as expressed by the Sharpe Ratio. The Sharpe Ratio is significantly different from the Sharpe Ratio of the unhedged portfolio. It can be concluded that the ANN-Bin strategy has significantly outperformed the benchmark strategies in the materials sector.

4.4.5.2. Industrials Sector

Table 4.13 shows the out-of-sample results of the binary ANN based hedging strategy and the benchmark strategies applied to the industrials sector. The out-of-sample simulation covers the period beginning in May 2005 to April 2010.

Metric	ANN-Bin	Unhedged	Always	Premium	Volatility
Net Profit	47.60%	-18.95%	-18.84%	-0.44%	-4.88%
Annualised Return	6.71%	-3.45%	-3.42%	-0.07%	-0.83%
Maximum Drawdown	-55.49%	-70.31%	-43.57%	-60.61%	-55.34%
Sharpe Ratio	0.46	-0.07	-0.21	0.09	0.04
Hedging Effectiveness	0.53	0.00	-0.14	0.16	0.11
Sortino Ratio	0.42	-0.03	-0.22	0.10	0.06
MAR Ratio	0.12	0.00	0.00	0.00	0.00
Ulcer Index	17.03	30.24	17.25	23.74	21.03
Ulcer Perf. Index	0.39	-0.11	-0.20	0.00	-0.04

Table 4.13.: Out-of-sample cross hedging: industrials sector

Table 4.14 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio.

The hypothesis for the Ledoit & Wolf (2008) test is:

$$H_0 : SR_{ANNBin} - SR_{Unhedged} = 0$$
$$H_1 : SR_{ANNBin} - SR_{Unhedged} \neq 0$$

The test statistic for the ANN-Bin hedging system does not allow the rejection of the null hypothesis at the 5% level and concludes that the Sharpe Ratio of the ANN-Bin hedging

Metric	ANN-Bin	Unhedged Portfolio
Mean Monthly Return	0.68	-0.11
Standard Deviation	5.16	5.81
Sharpe Ratio	0.46	-0.07

Table 4.14.: Statistics ANN-Bin vs. unhedged portfolio return: industrials sector

system is not significantly different from the unhedged portfolio position. Specifically, test statistic = 2.527 , p = 0.0939 (> 0.05), two tailed.

The industrials sector was one of the strongest affected sectors by the global financial crisis with a maximum drawdown of -70.31%. The ANN-Bin strategy was able to reduce this drawdown to -55.49%.

In addition, the ANN-Bin strategy achieved the highest annual return compared and the best risk-adjusted return compared to the benchmark strategies. In fact, the ANN-Bin strategy was the only strategy which achieved a positive net profit over the out-of-sample period.

Overall, the ANN-Bin hedging strategy had a good performance in terms of risk-adjusted return as expressed by the Sharpe Ratio. It can be concluded that the ANN-Bin strategy has outperformed the benchmark strategies in the industrials sector.

4.4.5.3. Consumer Discretionary Sector

Table 4.15 shows the out-of-sample results of the binary ANN based hedging strategy and the benchmark strategies applied to the consumer discretionary sector. The out-of-sample simulation covers the period beginning in May 2005 to April 2010.

Metric	ANN-Bin	Unhedged	Always	Premium	Volatility
Net Profit	23.95%	-22.39%	-22.70%	-8.09%	-11.47%
Annualised Return	3.65%	-4.14%	-4.21%	-1.40%	-2.01%
Maximum Drawdown	-54.24%	-68.08%	-49.18%	-58.29%	-52.10%
Sharpe Ratio	0.30	-0.12	-0.26	0.00	-0.04
Hedging Effectiveness	0.42	0.00	-0.14	0.12	0.08
Sortino Ratio	0.31	-0.13	-0.35	-0.01	-0.07
MAR Ratio	0.07	0.00	0.00	0.00	0.00
Ulcer Index	20.00	31.15	22.92	25.44	23.08
Ulcer Perf. Index	0.18	-0.13	-0.18	-0.05	-0.09

Table 4.15.: Out-of-sample cross hedging: consumer discretionary sector

Table 4.16 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio.

The hypothesis for the Ledoit & Wolf (2008) test is:

$$H_0 : SR_{ANNBin} - SR_{Unhedged} = 0$$
$$H_1 : SR_{ANNBin} - SR_{Unhedged} \neq 0$$

The test statistic for the ANN-Bin hedging system does not allow the rejection of the null hypothesis at the 5% level and concludes that the Sharpe Ratio of the ANN-Bin hedging

Metric	ANN-Bin	Unhedged Portfolio
Mean Monthly Return	0.42	-0.19
Standard Deviation	4.90	5.57
Sharpe Ratio	0.30	-0.12

Table 4.16.: Statistics ANN-Bin vs. unhedged portfolio return: consumer discretionary sector

system is not significantly different from the unhedged portfolio position. Specifically, test statistic = 2.944 , p = 0.0949 (> 0.05), two tailed.

The consumer discretionary sector is also among the strongest affected sectors by the global financial crisis with a maximum drawdown of -68.08%. While the S&P/ASX 200 index achieved a net profit of 17.45% and an annualised return of 2.72%, the consumer discretionary sector did not recover as well from the crisis.

During the out-of-sample period the unhedged portfolio resulted in a net loss of -22.39% and an annualised return of -4.14%.

In contrast, the ANN-Bin hedging strategy was able to dampen the effects of the financial crisis with an annualised return of 3.65% and a maximum drawdown of -54.24% achieving the highest risk-adjusted return among the benchmark strategies.

Overall, the ANN-Bin hedging strategy had a good performance in terms of risk-adjusted return as expressed by the Sharpe Ratio. It can be concluded that the ANN-Bin strategy has outperformed the benchmark strategies in the consumer discretionary sector.

4.4.5.4. Financial Sector

Table 4.17 shows the out-of-sample results of the binary ANN based hedging strategy and the benchmark strategies applied to the financial sector. The out-of-sample simulation covers the period beginning in May 2005 to April 2010.

Metric	**ANN-Bin**	**Unhedged**	**Always**	**Premium**	**Volatility**
Net Profit	70.51%	-1.83%	-1.68%	20.32%	23.20%
Annualised Return	9.32%	-0.31%	-0.28%	3.14%	3.54%
Maximum Drawdown	-46.57%	-63.86%	-40.71%	-51.56%	-46.06%
Sharpe Ratio	0.68	0.07	0.03	0.28	0.31
Hedging Effectiveness	0.61	0.00	-0.04	0.21	0.24
Sortino Ratio	0.64	0.09	0.02	0.25	0.29
MAR Ratio	0.20	0.00	0.00	0.06	0.08
Ulcer Index	13.19	26.62	15.82	18.58	16.23
Ulcer Perf. Index	0.71	-0.01	-0.02	0.17	0.22

Table 4.17.: Out-of-sample cross hedging: financial sector

Table 4.18 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio.

The hypothesis for the Ledoit & Wolf (2008) test is:

$$H_0 : SR_{ANNBin} - SR_{Unhedged} = 0$$
$$H_1 : SR_{ANNBin} - SR_{Unhedged} \neq 0$$

The test statistic for the ANN-Bin hedging system does not allow the rejection of the null hypothesis at the 5% level and concludes that the Sharpe Ratio of the ANN-Bin hedging

Metric	ANN-Bin	Unhedged Portfolio
Mean Monthly Return	0.83	0.09
Standard Deviation	4.25	4.78
Sharpe Ratio	0.68	0.07

Table 4.18.: Statistics ANN-Bin vs. unhedged portfolio return: financial sector

system is not significantly different from the unhedged portfolio position. Specifically, test statistic = 2.211 , p = 0.0682 (> 0.05), two tailed.

Although being strongly affected by the financial crisis with a maximum drawdown of -63.86%, the financial sector was able to recover from the drawdown resulting a net loss of -1.83%.

The ANN-Bin hedging strategy was able reduce the overall drawdown to -46.57%. In addition, the ANN-Bin strategy proved to have a good timing mechanism since it was able to capture the market recovery resulting in a net profit of 70.51% and an annualised return of 9.32% over the five year out-of-sample period.

Overall, the ANN-Bin hedging strategy had an excellent performance in terms of risk-adjusted return as expressed by the Sharpe Ratio. It can be concluded that the ANN-Bin strategy has outperformed the benchmark strategies in the financial sector.

4.4.5.5. Information Technology Sector

Table 4.19 shows the out-of-sample results of the binary ANN based hedging strategy and the benchmark strategies applied to the information technology sector. The out-of-sample simulation covers the period beginning in May 2005 to April 2010.

Metric	ANN-Bin	Unhedged	Always	Premium	Volatility
Net Profit	157.04%	89.12%	68.67%	92.45%	96.12%
Annualised Return	17.07%	11.22%	9.12%	11.55%	11.90%
Maximum Drawdown	-38.24%	-50.53%	-42.96%	-42.35%	-39.63%
Sharpe Ratio	0.78	0.57	0.49	0.58	0.61
Hedging Effectiveness	0.21	0.00	-0.08	0.01	0.04
Sortino Ratio	0.93	0.70	0.82	0.70	0.91
MAR Ratio	0.45	0.22	0.21	0.27	0.30
Ulcer Index	12.31	18.57	14.23	15.67	14.30
Ulcer Perf. Index	1.39	0.60	0.64	0.74	0.83

Table 4.19.: Out-of-sample cross hedging: information technology sector

Table 4.20 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio.

The hypothesis for the Ledoit & Wolf (2008) test is:

$$H_0 : SR_{ANNBin} - SR_{Unhedged} = 0$$
$$H_1 : SR_{ANNBin} - SR_{Unhedged} \neq 0$$

The test statistic for the ANN-Bin hedging system does not allow the rejection of the null hypothesis at the 5% level and concludes that the Sharpe Ratio of the ANN-Bin hedging

Metric	ANN-Bin	Unhedged Portfolio
Mean Monthly Return	1.56	1.13
Standard Deviation	6.91	6.91
Sharpe Ratio	0.78	0.57

Table 4.20.: Statistics ANN-Bin vs. unhedged portfolio return: information technology sector

system is not significantly different from the unhedged portfolio position. Specifically, test statistic = 2.808 , p = 0.084 (> 0.05), two tailed.

The information technology sector had a strong overall performance despite a maximum drawdown of -50.53%. The net profit was 89.12% and the annualised return was 11.22% in the out-of-sample period.

The ANN-Bin hedging strategy was able to improve the risk-adjusted return. The strategy achieved a net profit of 157.04% and annualised return of 17.07% while reducing the maximum drawdown to -38.24%.

Overall, the ANN-Bin hedging strategy had an excellent performance in terms of risk-adjusted return as expressed by the Sharpe Ratio. It can be concluded that the ANN-Bin strategy has outperformed the benchmark strategies in the information technology sector.

4.5. Continuous hedging approach

4.5.1. Introduction

In the following section the continuous hedging approach is evaluated using five years out-of-sample data beginning in May 2005 to April 2010. The objective is evaluate the performance of the continuous hedging strategy using Artificial Neural Networks. Similar to the binary hedging approach, the continuous ANN based hedging technique analyses the current state of the stock market and gives an indication whether unfavourable market conditions are expected or not.

If good conditions are expected, it is not necessary to hedge and therefore the portfolio of stocks is left unprotected. If however the market timing ANN predicts unfavourable market conditions, the portfolio needs to be protected by short selling stock index futures. The term continuous refers to the fact that the hedge ratio is regularly adjusted according to the strength of the ANN output signal. The strength can vary between 0% and 100%.

4.5.2. Output postprocessing

Table 4.21 lists the in-sample output range categorised into percentiles. For each output range the average monthly in-sample return is listed.

The continuous ANN based hedging strategy always hedges the portfolio. Market data is evaluated and then the hedge ratio is calculated based on the output of the ANN as shown in table 4.21. Based on the ANN output, a percentage from 0% to 100% is chosen, where 100% means that the portfolio is fully hedged and 0% means that the portfolio is not hedged at all. The continuous hedging approach allows to adjust the hedge ratio according to the strength of the ANN output signal.

Hedging strength	**Output range (x)**	**Average return (%)**	**# Obs**
100%	x <= -37.72	-5.93	82
90%	-37.72 < x <= -21.67	-2.87	81
80%	-21.67 < x <= -11.07	-1.53	82
70%	-11.07 < x <= -4.88	-0.48	82
60%	-4.88 < x <= 2.88	0.03	81
50%	2.88 < x <= 11.17	0.71	82
40%	11.17 < x <= 19.05	1.46	82
30%	19.05 < x <= 24.26	2.32	81
20%	24.26 < x <= 28.99	2.41	82
10%	28.99 < x <= 36.75	3.44	82
0%	36.75 < x	5.02	81

Table 4.21.: Hedging strength vs. ANN forecast

The percentages shown in table 4.21 have been assigned based on the in-sample output range of the ANN. The ANN outputs have been categorized into percentiles so that the categories are equally distributed across the in-sample range. Then the percentages have been assigned starting with 100% hedging strength for the category with the worst average return forecast up to 0% hedging strength for the category with the best return forecast.

For example, an ANN output of 25 means that 20% of the portfolio is protected by the hedging strategy and -15 means that 80% of the portfolio is protected.

4.5.3. Out-of-sample results S&P/ASX 200

Table 4.22 reports the out-of-sample hedging results for the S&P/ASX 200 index. The out-of-sample period uses data beginning in May 2005 to April 2010. The continuous hedging strategy based on Artificial Neural Networks is called ANN-Cont. The performance is compared to the basic strategies of always hedging and leaving the portfolio unhedged. As explained in the methodology section, hedging strategies based on the futures premium and volatility are used in addition to the basic benchmark strategies.

Metric	ANN-Cont	Unhedged	Always	Premium	Volatility
Net Profit	106.35%	17.45%	16.46%	50.52%	49.41%
Annualised Return	12.85%	2.72%	2.58%	7.06%	6.93%
Maximum Drawdown	-26.15%	-53.64%	-27.23%	-35.90%	-26.07%
Sharpe Ratio	1.31	0.26	0.42	0.70	0.74
Hedging Effectiveness	1.05	0.00	0.16	0.44	0.48
Sortino Ratio	1.63	0.36	0.51	0.58	0.85
MAR Ratio	0.49	0.05	0.09	0.20	0.27
Ulcer Index	6.34	21.76	10.19	11.53	8.29
Ulcer Perf. Index	2.03	0.13	0.25	0.61	0.84

Table 4.22.: Out-of-sample trading metrics: Continuous hedging

Table 4.23 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio. The Ledoit & Wolf (2008) block-wise bootstrapping test with a block interval of 5 and 5000 bootstrap replications was used to test the null hypothesis H_0 that the difference of Sharpe ratios is zero. The alternative H_1 is that the difference is not zero. The Ledoit & Wolf (2008) has been specifically designed for the purpose of comparing two Sharpe Ratios.

The hypothesis for the Ledoit & Wolf (2008) test is:

$H_0 : SR_{ANNBin} - SR_{Unhedged} = 0$
$H_1 : SR_{ANNBin} - SR_{Unhedged} \neq 0$

Metric	**ANN Strategy**	**Unhedged Portfolio**
Mean Monthly Return	1.05	0.31
Standard Deviation	2.78	4.05
Sharpe Ratio	1.32	0.26

Table 4.23.: Continuous ANN hedging strategy return vs. unhedged portfolio return

The test statistic for the ANN-Cont hedging system allows the rejection of the null hypothesis at the 5% level and concludes that the Sharpe Ratio of the ANN-Cont hedging system is significantly different from the unhedged portfolio position. Specifically, test statistic = 5.267 , p = 0.0352 (< 0.05), two tailed.

The ANN-Cont hedging strategy was able to reduce the maximum drawdown of the unhedged portfolio from -53.64% to -26.15%. In terms of the Ulcer Index, which is a measure for the severity and duration of drawdowns, the ANN-Cont strategy was able to achieve an improvement. In terms of risk-adjusted return as measured by the Sharpe Ratio, MAR Ratio, and Ulcer Performance Index the ANN-Cont strategy achieved the best result compared to the benchmark strategies.

Overall, the ANN-Cont hedging strategy had an excellent performance in terms of risk-adjusted return. The Sharpe Ratio is significantly different from the Sharpe Ratio of the unhedged portfolio. It can be concluded that the ANN-Cont strategy has outperformed the benchmark strategies in the S&P/ASX 200 index.

4.5.4. Out-of-sample results cross hedging

The evaluation of the proposed continuous ANN based hedging strategy showed a better performance compared to the benchmark strategies in S&P/ASX 200 index. As discussed in section 4.3, the proposed machine learning technique will also be evaluated in terms of the following list of sector indices that fulfil minimum correlation requirements.

- Materials
- Industrials
- Consumer Discretionary
- Financial
- Information Technology

4.5.4.1. Materials Sector

Table 4.24 shows the out-of-sample results of the continuous ANN based hedging strategy and the benchmark strategies applied to the materials sector. The out-of-sample simulation covers the period beginning in May 2005 to April 2010.

Table 4.25 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio.

The hypothesis for the Ledoit & Wolf (2008) test is:

$H_0 : SR_{ANNCont} - SR_{Unhedged} = 0$
$H_1 : SR_{ANNCont} - SR_{Unhedged} \neq 0$

Metric	ANN-Cont	Unhedged	Always	Premium	Volatility
Net Profit	239.55%	70.86%	39.66%	132.03%	120.27%
Annualised Return	22.64%	9.35%	5.73%	15.09%	14.09%
Maximum Drawdown	-41.99%	-58.91%	-39.06%	-45.13%	-31.46%
Sharpe Ratio	1.28	0.53	0.41	0.92	0.90
Hedging Effectiveness	0.75	0.00	-0.12	0.39	0.37
Sortino Ratio	2.01	0.81	0.71	1.46	1.79
MAR Ratio	0.54	0.16	0.15	0.33	0.45
Ulcer Index	9.45	21.15	15.88	12.59	7.76
Ulcer Perf. Index	2.40	0.44	0.36	1.20	1.82

Table 4.24.: Out-of-sample cross hedging: materials sector

Metric	ANN-Cont	Unhedged Portfolio
Mean Monthly Return	1.83	0.94
Standard Deviation	4.95	6.11
Sharpe Ratio	1.28	0.53

Table 4.25.: Statistics ANN-Cont vs. unhedged portfolio return: materials sector

The test statistic for the ANN-Cont hedging system allows the rejection of the null hypothesis at the 1% level and concludes that the Sharpe Ratio of the ANN-Cont hedging system is significantly different from the unhedged portfolio position. Specifically, test statistic = 4.399 , $p = 0.0044$ (< 0.01), two tailed.

The materials sector achieved a net profit of 70.86% over the anlysed period. In comparison, the S&P/ASX 200 resulted in a net profit of 17.45%.

In terms of maximum drawdown, the materials sector had a drawdown of -58.91% and the S&P/ASX 200 index had a drawdown of -53.64%.

The ANN-Cont strategy was able to reduce the maximum drawdown from -58.91% to -41.99% while increasing the net profit to 239.55% and annual return to 22.64%. Out of the analysed hedging strategies, the ANN-Cont strategy had the best risk-adjusted return over the out-of-sample period.

Overall, the ANN-Cont hedging strategy had an excellent performance in terms of risk-adjusted return as expressed by the Sharpe Ratio. The Sharpe Ratio is significantly different from the Sharpe Ratio of the unhedged portfolio. It can be concluded that the ANN-Cont strategy has outperformed the benchmark strategies in the materials sector.

4.5.4.2. Industrials Sector

Table 4.26 shows the out-of-sample results of the continuous ANN based hedging strategy and the benchmark strategies applied to the industrials sector. The out-of-sample simulation covers the period beginning in May 2005 to April 2010.

Metric	ANN-Cont	Unhedged	Always	Premium	Volatility
Net Profit	49.94%	-18.95%	-18.84%	-0.44%	-4.88%
Annualised Return	7.00%	-3.45%	-3.42%	-0.07%	-0.83%
Maximum Drawdown	-50.47%	-70.31%	-43.57%	-60.61%	-55.34%
Sharpe Ratio	0.48	-0.07	-0.21	0.09	0.04
Hedging Effectiveness	0.55	0.00	-0.14	0.16	0.11
Sortino Ratio	0.52	-0.03	-0.22	0.10	0.06
MAR Ratio	0.14	0.00	0.00	0.00	0.00
Ulcer Index	14.67	30.24	17.25	23.74	21.03
Ulcer Perf. Index	0.48	-0.11	-0.20	0.00	-0.04

Table 4.26.: Out-of-sample cross hedging: industrials sector

Table 4.27 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio.

The hypothesis for the Ledoit & Wolf (2008) test is:

$$H_0 : SR_{ANNCont} - SR_{Unhedged} = 0$$
$$H_1 : SR_{ANNCont} - SR_{Unhedged} \neq 0$$

The test statistic for the ANN-Cont hedging system does not allow the rejection of the null hypothesis at the 5% level and concludes that the Sharpe Ratio of the ANN-Cont hedging system is not significantly different from the unhedged portfolio position. Specifically, test statistic = 3.056 , p = 0.0592 (> 0.05), two tailed.

Metric	ANN-Cont	Unhedged Portfolio
Mean Monthly Return	0.69	-0.11
Standard Deviation	5.05	5.81
Sharpe Ratio	0.48	-0.07

Table 4.27.: Statistics ANN-Cont vs. unhedged portfolio return: industrials sector

The industrials sector was one of the strongest affected sectors by the global financial crisis with a maximum drawdown of -70.31%. The ANN-Cont strategy was able to reduce this drawdown to -50.47%

In addition, the ANN-Cont strategy achieved the highest annual return compared and the best risk-adjusted return compared to the benchmark strategies.

Overall, the ANN-Cont hedging strategy had an excellent performance in terms of risk-adjusted return as expressed by the Sharpe Ratio. It can be concluded that the ANN-Cont strategy has outperformed the benchmark strategies in the industrials sector.

4.5.4.3. Consumer Discretionary Sector

Table 4.28 shows the out-of-sample results of the continuous ANN based hedging strategy and the benchmark strategies applied to the consumer discretionary sector. The out-of-sample simulation covers the period beginning in May 2005 to April 2010.

Metric	ANN-Cont	Unhedged	Always	Premium	Volatility
Net Profit	23.75%	-22.39%	-22.70%	-8.09%	-11.47%
Annualised Return	3.62%	-4.14%	-4.21%	-1.40%	-2.01%
Maximum Drawdown	-51.82%	-68.08%	-49.18%	-58.29%	-52.10%
Sharpe Ratio	0.30	-0.12	-0.26	0.00	-0.04
Hedging Effectiveness	0.42	0.00	-0.14	0.12	0.08
Sortino Ratio	0.35	-0.13	-0.35	-0.01	-0.07
MAR Ratio	0.07	0.00	0.00	0.00	0.00
Ulcer Index	19.63	31.15	22.92	25.44	23.08
Ulcer Perf. Index	0.18	-0.13	-0.18	-0.05	-0.09

Table 4.28.: Out-of-sample cross hedging: consumer discretionary sector

Table 4.29 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio.

The hypothesis for the Ledoit & Wolf (2008) test is:

$$H_0 : SR_{ANNCont} - SR_{Unhedged} = 0$$
$$H_1 : SR_{ANNCont} - SR_{Unhedged} \neq 0$$

The test statistic for the ANN-Cont hedging system does not allow the rejection of the null hypothesis at the 5% level and concludes that the Sharpe Ratio of the ANN-Cont hedging system is not significantly different from the unhedged portfolio position. Specifically, test statistic = 3.03 , p = 0.0918 (> 0.05), two tailed.

Metric	ANN-Cont	Unhedged Portfolio
Mean Monthly Return	0.41	-0.19
Standard Deviation	4.75	5.57
Sharpe Ratio	0.30	-0.12

Table 4.29.: Statistics ANN-Cont vs. unhedged portfolio return: consumer discretionary sector

The consumer discretionary sector was also among the strongest affected sectors by the global financial crisis with a maximum drawdown of -68.08%. While the S&P/ASX 200 index achieved a net profit of 17.45% and an annualised return of 2.72%, the consumer discretionary sector did not recover as well from the crisis.

During the out-of-sample period the unhedged portfolio resulted in a net loss of -22.39% and an annualised return of -4.14%.

In contrast, the ANN-Cont hedging strategy was able to dampen the effects of the financial crisis with an annualised return of 3.62% and a maximum drawdown of -51.82% achieving the highest risk-adjusted return among the benchmark strategies.

Overall, the ANN-Cont hedging strategy had an good performance in terms of risk-adjusted return as expressed by the Sharpe Ratio. It can be concluded that the ANN-Cont strategy has outperformed the benchmark strategies in the consumer discretionary sector.

4.5.4.4. Financial Sector

Table 4.30 shows the out-of-sample results of the continuous ANN based hedging strategy and the benchmark strategies applied to the financial sector sector. The out-of-sample simulation covers the period beginning in May 2005 to April 2010.

Metric	**ANN-Cont**	**Unhedged**	**Always**	**Premium**	**Volatility**
Net Profit	72.58%	-1.83%	-1.68%	20.32%	23.20%
Annualised Return	9.54%	-0.31%	-0.28%	3.14%	3.54%
Maximum Drawdown	-41.91%	-63.86%	-40.71%	-51.56%	-46.06%
Sharpe Ratio	0.72	0.07	0.03	0.28	0.31
Hedging Effectiveness	0.65	0.00	-0.04	0.21	0.24
Sortino Ratio	0.70	0.09	0.02	0.25	0.29
MAR Ratio	0.23	0.00	0.00	0.06	0.08
Ulcer Index	11.16	26.62	15.82	18.58	16.23
Ulcer Perf. Index	0.85	-0.01	-0.02	0.17	0.22

Table 4.30.: Out-of-sample cross hedging: financial sector

Table 4.31 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio.

The hypothesis for the Ledoit & Wolf (2008) test is:

$$H_0 : SR_{ANNCont} - SR_{Unhedged} = 0$$
$$H_1 : SR_{ANNCont} - SR_{Unhedged} \neq 0$$

The test statistic for the ANN-Cont hedging system allows the rejection of the null hypothesis at the 5% level and concludes that the Sharpe Ratio of the ANN-Cont hedging system is significantly different from the unhedged portfolio position. Specifically, test statistic = 2.545 , p = 0.0498 (< 0.05), two tailed.

Metric	ANN-Cont	Unhedged Portfolio
Mean Monthly Return	0.84	0.09
Standard Deviation	4.03	4.78
Sharpe Ratio	0.72	0.07

Table 4.31.: Statistics ANN-Cont vs. unhedged portfolio return: financial sector

Although being strongly affected by the financial crisis with a maximum drawdown of -63.86%, the financial sector was able to recover from the drawdown resulting a net loss of -1.83%.

The ANN-Cont hedging strategy was able reduce the overall drawdown to -41.91%. In addition, the ANN-Cont strategy proved to have a good timing mechanism since it was able to capture the market recovery resulting in a net profit of 72.58% and an annualised return of 9.54% over the five year out-of-sample period.

Overall, the ANN-Cont hedging strategy had an excellent performance in terms of risk-adjusted return as expressed by the Sharpe Ratio. The Sharpe Ratio is significantly different from the Sharpe Ratio of the unhedged portfolio. It can be concluded that the ANN-Cont strategy has outperformed the benchmark strategies in the financial sector.

4.5.4.5. Information Technology Sector

Table 4.32 shows the out-of-sample results of the continuous ANN based hedging strategy and the benchmark strategies applied to the information technology sector. The out-of-sample simulation covers the period beginning in May 2005 to April 2010.

Metric	ANN-Cont	Unhedged	Always	Premium	Volatility
Net Profit	161.28%	89.12%	68.67%	92.45%	96.12%
Annualised Return	17.39%	11.22%	9.12%	11.55%	11.90%
Maximum Drawdown	-37.84%	-50.53%	-42.96%	-42.35%	-39.63%
Sharpe Ratio	0.80	0.57	0.49	0.58	0.61
Hedging Effectiveness	0.23	0.00	-0.08	0.01	0.04
Sortino Ratio	1.06	0.70	0.82	0.70	0.91
MAR Ratio	0.46	0.22	0.21	0.27	0.30
Ulcer Index	12.45	18.57	14.23	15.67	14.30
Ulcer Perf. Index	1.40	0.60	0.64	0.74	0.83

Table 4.32.: Out-of-sample cross hedging: information technology sector

Table 4.33 shows a statistical breakdown of the out-of-sample results for the ANN based hedging strategy compared to the unhedged portfolio.

The hypothesis for the Ledoit & Wolf (2008) test is:

$H_0 : SR_{ANNCont} - SR_{Unhedged} = 0$
$H_1 : SR_{ANNCont} - SR_{Unhedged} \neq 0$

The test statistic for the ANN-Cont hedging system allows the rejection of the null hypothesis at the 5% level and concludes that the Sharpe Ratio of the ANN-Cont hedging system is significantly different from the unhedged portfolio position. Specifically, test statistic = 3.347 , p = 0.023 (< 0.05), two tailed.

Metric	ANN-Cont	Unhedged Portfolio
Mean Monthly Return	1.58	1.13
Standard Deviation	6.83	6.91
Sharpe Ratio	0.80	0.57

Table 4.33.: Statistics ANN-Cont vs. unhedged portfolio return: information technology sector

The information technology sector had a strong overall performance despite a maximum drawdown of -50.53%. The net profit was 89.12% and the annualised return was 11.22% in the out-of-sample period.

The ANN-Cont hedging strategy was able to improve the risk-adjusted return. The strategy achieved a net profit of 161.28% and annualised return of 17.39% while reducing the maximum drawdown to -37.84%.

Overall, the ANN-Cont hedging strategy had an excellent performance in terms of risk-adjusted return as expressed by the Sharpe Ratio. The Sharpe Ratio is significantly different from the Sharpe Ratio of the unhedged portfolio. It can be concluded that the ANN-Cont strategy has outperformed the benchmark strategies in the information technology sector.

4.6. Summary of results

Figure 4.8 gives an overview of the Sharpe Ratios for each hedging strategy.

In the S&P/ASX 200 index all of the analysed hedging strategies achieved a higher Sharpe Ratio compared to the unhedged portfolio. The two proposed ANN based hedging strategies achieved the highest Sharpe Ratios. The ANN-Cont strategy was the best performing strategy of all the analysed strategies and was able to achieve a slight improvement on the ANN-Bin strategy.

In terms of the unhedged portfolios, the materials and information technology sectors had a better performance than the overall market.

The industrials and consumer discretionary sectors ended in a net loss over the analysed five year out-of-sample period which led to negative Sharpe Ratio. The two ANN based strategies were able to achieve a net gain over the same period and were able to improve the risk-adjusted return.

Out of the six analysed indices, the ANN-Cont strategy achieved a slightly higher Sharpe Ratio in five instances compared to the ANN-Bin strategy. In the consumer discretionary sector, both strategies achieved the same Sharpe Ratio.

Overall, the two ANN based hedging strategies achieved a better risk-adjusted return across the analysed sectors. The Ledoit & Wolf (2008) bootstrapping test showed that the results are robust and statistically significant. Therefore, it can be concluded that the ANN based strategies outperformed the benchmark strategies in the out-of-sample period.

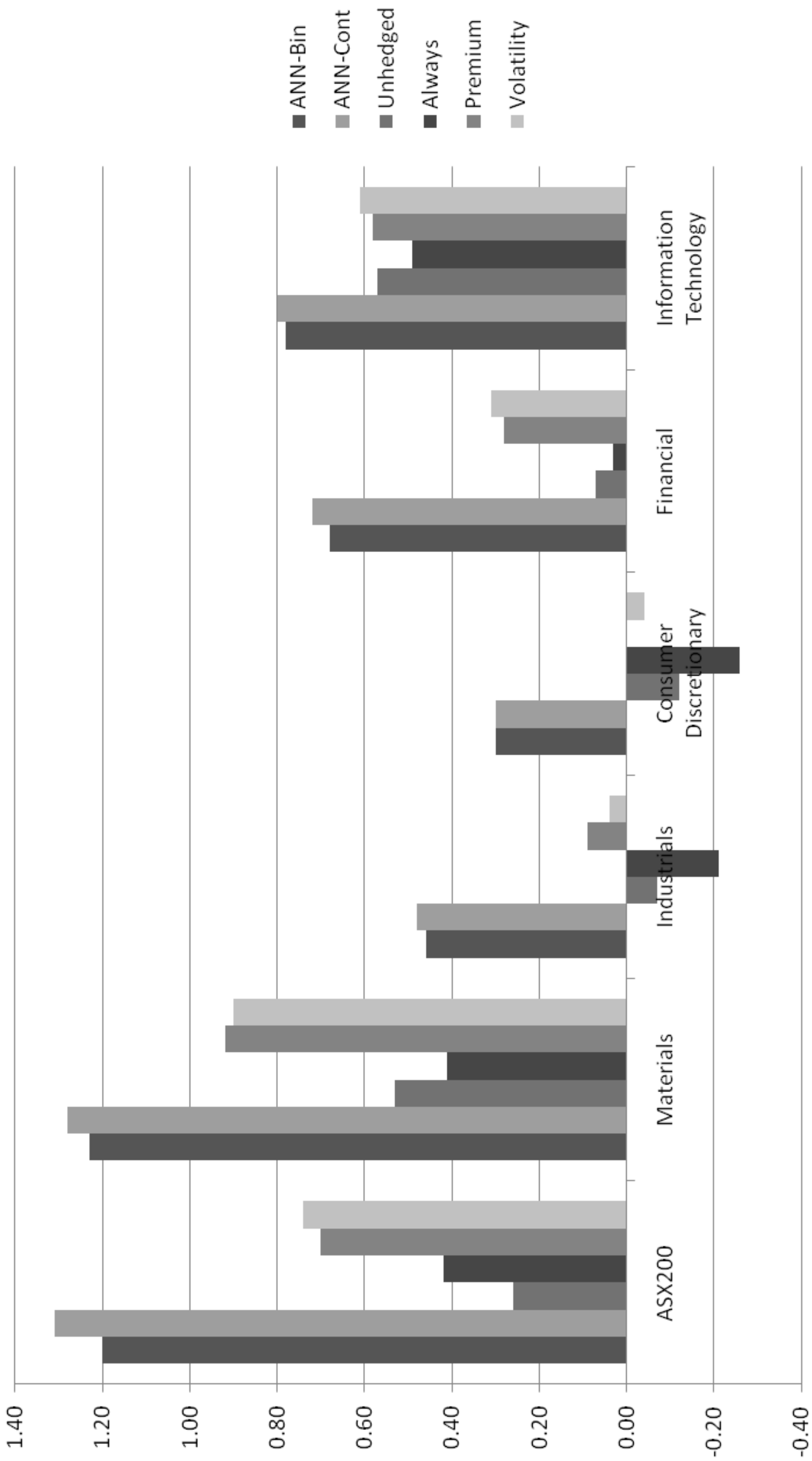

Figure 4.8.: Overview of Sharpe Ratios in out-of-sample period

5. Conclusion

This chapter summarizes the thesis motivation and results and draws conclusions regarding the research question. In addition, possible future research directions are discussed.

5.1. Thesis summary

This thesis proposed an ANN enhanced decision support system for financial risk management. The decision-support system allowed to increase the expected return while practising the hedge against unfavourable movements in the stock market.

The literature review revealed that there is a large number of studies trying to forecast movements in the stockmarket, but there is a lack of literature trying to improve stock market risk management strategies with machine learning techniques.

The contribution of this research was to fill this gap by applying the existing body of literature in stock index forecasting with machine learning techniques to the domain of portfolio risk management. This thesis analysed whether strategies used to predict movements in the stock index can also be used to derive hedging strategies and improve the overall risk-return trade off an investor faces.

In particular, a new market timing model based on artificial neural networks was developed which formed the heart of the proposed decision support system. The system analysed stockmarket and futures data and made a prediction about expected stock market conditions one month ahead. Depending on the ANN output, a decision was made whether it was necessary to hedge a portfolio or not. If hedging was necessary, the hedge ratio was estimated in a second step. The proposed ANN based hedging strategy used stock index futures to protect the portfolio against downturns in the share market.

The contribution which results from developing the proposed model stems from the fact that the model directly addressed the gap in the literature mentioned earlier. In addition, it was shown that the model achieved a significant improvement in the risk-return tradeoff compared to the benchmark hedging strategies in the Australian stockmarket.

The importance of the research stems from the fact that hedging can be used to reduce the risk associated with adverse price movements in the stock market. The aim of risk management and hedging in particular is to control or reduce the risk of adverse price movements. Stock index futures offer the opportunity to manage the market risk of investment portfolios. Hedging is an important tool for institutions like banks and superannuation funds to manage risks associated with stock market investments.

If an investor is uncertain about the economic situation, but thinks that a portfolio has been chosen well and will outperform the market, financial derivatives like stock index futures can be used to protect the portfolio against downturns that affect the market as a whole. The hedged portfolio is then not affected by market moves and is only exposed to the performance relative to the market. A naive strategy of selling the whole portfolio temporarily and buying it back later might lead to significant transactions costs. Stock index futures can be used for short-term protection in uncertain market conditions. (Hull 2008)

In general, stock market participants face the problem of having to make estimates about future directions of the stock market and face the uncertainty of not knowing when and how long to hedge. This thesis intended to contribute to the solution to this problem by applying the existing body of stock index forecasting literature to the domain of dynamic portfolio hedging.

This thesis addressed the research question in the context of a 10 year period of Australian stock market data (ASX 200) and was able to show that artificial neural networks can be used to improve risk management strategies.

An additional contribution of this thesis was the design of an automated neural network training algorithm which used financial metrics instead of statistical metrics as a stopping criterion. The benefit of the automated neural network training is that no human intervention is necessary which speeds up the training process. This can be very useful when the time-frame for ANN training is limited, e.g. if the ANN needs to be retrained between the close of the stock market and the opening on the next day. The uniqueness of the proposed algorithm lies in the fact that it is able to automatically determine a suitable ANN structure based on a financial trading metric like the Sharpe Ratio.

Finally, a methodology for building and testing hedging strategies using ANNs has been developed by extending the methodology of Vanstone & Finnie (2009) to the domain of portfolio risk management.

5.2. Conclusion regarding the research problem

As discussed in the methodology section, the main goal of this thesis is to evaluate whether artificial neural networks are suitable decision support tools in the domain of portfolio risk management. Two hypothesis have been stated in order to address the research problem. These hypotheses are restated in the following sections and an answer to the following research question will be given.

”Can artificial neural networks be used to improve the effectiveness of dynamic hedging strategies in the Australian stockmarket?”

5.2.1. Conclusion regarding hypothesis 1

Hypothesis 1:

Dynamic hedging strategies based on artificial neural networks that use a binary hedging method can improve the effectiveness in relation to conventional hedging strategies.

Conclusions about hypothesis 1 can be drawn after considering the results of ANN-Bin hedging strategy. The ANN-Bin hedging strategy was applied to the S&P/ASX 200 index and five sector indices. In the S&P/ASX 200 index the ANN-Bin strategy achieved a significantly higher net return compared to the unhedged portfolio while reducing the maximum drawdown from -53.64% to -31.72%.

In all the analysed markets, the ANN-Bin strategy was able to achieve a better Sharpe Ratio compared to the benchmark strategies.

For the S&P/ASX 200 index the Ledoit & Wolf (2008) test showed that the risk adjusted return of the ANN-Bin strategy is significantly better than the risk adjusted return of the unhedged portfolio.

It therefore can be concluded that the binary ANN based hedging strategy was able to outperform the benchmark strategies in the analysed markets.

5.2.2. Conclusion regarding hypothesis 2

Hypothesis 2:

Dynamic hedging strategies based on artificial neural networks that use a continuous hedging method can improve the effectiveness in relation to conventional hedging strategies.

Conclusions about hypothesis 2 can be drawn after considering the results of ANN-Cont hedging strategy. Similar to the ANN-Bin strategy, the ANN-Cont hedging strategy was applied to the S&P/ASX 200 index and five sector indices. In the S&P/ASX 200 index the ANN-Cont strategy achieved a significantly higher net return compared to the unhedged portfolio while reducing the maximum drawdown from -53.64% to -26.15%.

In all the analysed markets, the ANN-Cont strategy was able to achieve a better Sharpe Ratio compared to the benchmark strategies.

For the S&P/ASX 200 index the Ledoit & Wolf (2008) test showed that the risk adjusted return of the ANN-Cont strategy is significantly better than the risk adjusted return of the unhedged portfolio.

It therefore can be confidently concluded that the continuous ANN based hedging strategy was able to outperform the benchmark strategies in the analysed markets.

5.2.3. Conclusion regarding the research question

The research question stated stated earlier was:

”Can artificial neural networks be used to improve the effectiveness of dynamic hedging strategies in the Australian stockmarket?”

Overall, the two analysed artificial neural network based hedging strategies achieved a better risk-adjusted return across the analysed sectors. The Ledoit & Wolf (2008) bootstrapping test showed that the results are robust and statistically significant. Therefore, it can be concluded that artificial neural networks can be used to improve the effectiveness of dynamic hedging strategies in the Australian stockmarket.

5.3. Future Research

This thesis has proposed a ANN enhanced decision support system that allowed hedgers to maximise their expected return while practising the hedge against unfavourable movements in the stock market.

As part of the contribution of this thesis a methodology for the training and evaluation of machine learning based hedging strategies has been created.

Artificial neural networks have been chosen as primary machine learning technique since the literature review revealed that artificial neural networks are established and suitable in the area of financial time series prediction. However, it has also been shown that the current trend in the literature is to combine ANNs with technologies like evolutionary algorithms into hybrid systems to further enhance the prediction accuracy. In future research the described methodology could be applied to hybrid machine learning models to evaluate their performance.

A further contribution of this thesis was the creation of an automated ANN training technique which used a financial metric (Sharpe Ratio) instead of a statistical metric (MSE) as early stopping criterion. In this thesis the proposed learning technique has been applied to the ANN training algorithm described by Vanstone & Finnie (2009). The algorithm sets the initial number of hidden ANN neurons to the square root of the number of ANN inputs. The number of hidden neurons is then increased during the ANN training until an increase in the number of hidden neurons fails to further increase the in-sample performance.

The algorithm described by Vanstone & Finnie (2009) is good since the authors showed that it provides good results in training ANNs for stockmarket forecasting and it gives researchers a practical guideline in the resource intensive process of neural network training. However, the automated ANN training technique proposed in this thesis allows to train a large variety of neural networks and evaluate their performance. In future research it could be investigated if increasing the number of hidden neurons further would lead to an even better performance. The automated nature of the training process allows the comparison of a variety of algorithms which was only possible within limits before since configuring and training each ANN separately is very time consuming.

A limitation of this thesis was the use of stock indices as proxy for diversified portfolios. It would be interesting to evaluate the performance of actual trading strategies in combination with the proposed risk management model.

Artificial neural networks provide only a limited interpretability and therefore are often described as ”Block Box”. There is a variety of literature which attempts to extract rules from neural networks and create if-then-else rules which then can be examined, e.g. Mitsdorffer et al. (2002). It would be beneficial to be able to examine the decision making process in more detail so that investors can gain a greater confidence in the hedging decisions made.

Finally, the continuous ANN based hedging model showed that using the ANN output strength for determining how much of the portfolio should be hedged worked well during the analysed period. In future research, it would also be interesting to extend this approach to the area of managing position sizes in stock market trading systems. It needs to be investigated if using the ANN output strength as guidance in the money management process can improve the overall performance of trading strategies.

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Appendices

A. Appendix

A.1. Table of Abbreviations

In this thesis a number of abbreviations is used. The following table lists a number of the most important terms.

AORD	Australian All Ordinaries Index
ASX	Australian Securities Exchange
COMIT	Major Italian Bank (Banca Commerciale Italiana)
DAX	German Stock Exchange Index
DJIA	Dow Jones Industrial Average
FTSE	London Stock Exchange Index
IBEX	Spanish Stock Exchange Index
KOSPI	Korea Composite Stock Price Index
MAE	Maximum Adverse Excursion
NASDAQ	National Association of Securities Dealers Automated Quotation
NIFTY	National Stock Exchange of India
NIKKEI	Tokyo Stock Exchange Index
ROC	Rate of Change
STI	Straits Times Index
TOPIX	Tokyo Stock Exchange Index