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Application of Neural Networks in Stock Market Prediction

by

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Originality Statement

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Abstract

In the last 50 years life expectancy has increased by 30% [1] because of improvements in technology, medicine and standard of living. As a result, the need of support, and the financial strain from the aging population has grown. A profitable high performing investment strategy for retirement funds would be ideal to support individuals long after retirement. Currently, large superannuation funds utilise risk analysis, excel modelling and mathematical computations to calculate profitable investments. Within the field of computation science and mechatronic engineering artificial intelligence has flourished. An example of such a technique is neural networks, a modelling tool that is able to predict stock market fluctuations fairly accurately.

By utilising this prediction capability, combined with dynamic decision making methods, a system can be developed to provide long term profits for the aging population. The designed system loads historical data of the specified stock, trains a Neural Network on this input and then goes through a trading simulation based on the predictions and a range of decision methods. The system with initial testing proves to have a strong basis, however, risk is challenging to consider and the system is difficult to implement within a real trading environment. If this system is implemented correctly within a commission free trading environment, taking daily transactions it is expected to make up to 36% annual profit. These results have not only surpassed that available in the literature, the process undertaken has been across more stocks, a large range of decision methods and outlines the power of pure Neural Network prediction. Furthermore, the practical capability of a Neural Network trading system is outlined, this research is the link between the literature and a real trading market implementation.

Acknowledgements

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Chapter 1: Introduction

Artificial intelligence (AI), intelligence exhibited by a computing machine, is a growing area of success within Engineering and Computer Science as a result of increased computational processing power and improved programming languages. The ideal AI is a general purpose system that is able to undertake and learn any task. Currently technology is not at this level, but there are forms and concepts of code that can learn. Such a model is Artificial Neural Networks (ANN). Rather than hard coding complex logic and rules a Neural Network (NN) uses a system of connect nodes and weightings to simulate the function of a biological brain. Such a model is considered part of the AI family as the system is able to learn and improve through training. Currently they are used within a range of industries, from playing ‘GO’, agricultural prediction, facial recognition, fraud detection and many more. Rather than producing a linear function for data point association NNs develop a dynamic non-linear relationship that allows them to succeed in predictive tasks. Therefore, their potential within a range of business environments is clear, however, the structure, input designs and training methods all increase the complexity of the system and lead to difficulties in their application. Improvements in automated/wizard implementations along with the decrease in cost and increase in performance of personal computers has allowed for individuals and researchers to utilise them.

1 Motivation

An industry in which NN growth and use has been evident in recent years is the financial industry. Financial corporations are the second largest contributors to NN research, following close behind the military [2]. Society revolves around the requirement to trade resources to allow individuals to gain access to services and products, improving their standard of living. With improvements in quality of life and medical procedures life expectancy is dramatically increasing. As a result, there is increased strain from the aging population, unable to work and increasing economic pressures. Thus, the importance of long term, high return investment systems are essential in reducing this tension, allowing for wealth and support late into retirement. This issue drives the requirement and potential financial benefit of a long term, automated, low risk investment management system. Artificial intelligence has shown great potential in meeting this need.

The potential of NNs within the financial industry is clear as well as the potential benefit it would have to society. Thus, there has recently been increasing research within the area of investment and funds management. In the context of stock markets research has focused on different models, prediction accuracy and trading signals. There has been documentation outlining how to combine and build potential systems describing the best methodologies. However, there have been few examples or papers discussing actual practical trading systems, analysing their potential in profits or as an investment platform. The few papers that have been published on the topic have only been able to achieve profits of around 20-40% annually [3], [4], [5]. It is the intention of the author to design a system that surpasses this system and is implementable within a real trading environment.

2 Methodology

The proposed system will utilise NNs to predict the closing price of a specified stock, it will then use a decision engine to output an appropriate trading signal (buy/sell) and will finally evaluate the system over time, allowing for rigorous testing to ensure its accuracy and performance. To simplify analysis data will be categorised by the decision method; prediction, technical indicator, monthly trading and prediction/ technical indicator combination. Furthermore, grouping of the stocks will be based on industry and shape (increase, decreasing, trough and peaks). By building such an environment clear testing methodology will be established accessing pure NN prediction against technical indicators ability to produce long term wealth on the stock market. Verification of the final results will be achieved by assessing the simulation from a range of perspectives, addressing each trading method by; financial performance, risk and complexity, ensuring a holistic view.

3 Contribution

The body of research developed a decision trading system that is able to be profitable across all stock times; increasing, decreasing and erratic movements. The banking and energy industry were identified as a potential profit area of stock selection resulting in profits of above 50%. Furthermore, risk was evaluated of the trading system to find it is likely to make profit higher than a bank account investment 70% of the time. Prior research has been unable to assess the practical capabilities of such a system, focusing mainly on its accuracy and the trading strategy methods. By assessing practical metrics and parameters research indicates that a Neural Network trading platform would be both viable and profitable within a practical trading environment.

4 Thesis Outline

This document has been structured to ensure the reader is provided initially with a clear understanding of the topic, discussing NN history and their application within finance. In Chapter 3 the testing and design of the system has been outlined to provide insight into the workings of the trading algorithm, NN prediction, as well as the specified stock input and desired outputs. Chapter 4 provides a high level analysis of the collected results, giving an understanding of the initial findings. These are further analysed in Chapter 5 addressing why the results occurred and the interaction between them. Finally, the document concludes by summarising all findings and conveying methods for improving and furthering similar research in the future.

Chapter 2: Background

Stock market prediction initially began with simplistic formulas and calculations that aimed to simplify or provide indications of stock movement and direction. With the advent of computers and improvements in processing power there has been a clear trend to improved analysis and prediction techniques, initially being rule based, brute force evaluations, but have recently moved towards cognitive and machine learning based approaches. This is clear with association between stock market prediction and neural network research and the associated improvements. Price prediction using simplistic neural network models has risen to around 80% [5]. With such great success further development has been made towards decision methods using these values. However little implementation has been made with these systems into the practical market and consumers are still to receive benefits helping with their long term wealth and standard of living improvements.

Section 1: Stock Trading Strategy, establishes the context of what stock trading is, how one can make a living by doing so and the general principals. It goes into details of different strategies from the simplistic calculations of technical indicators to the complex models of movement prediction. Once the context of the research is defined, Section 2, looks at the vessel of prediction, Neural Networks; what they are, their history, their function and general structure. Section 3, addresses their role within the financial market, evaluating their predictive capability, possible trading strategies, a combination of the two elements and finally how these systems can be built and evaluated. The chapter concludes with Section 4, a summary of the discussed work.

1 Stock Trading Strategy

Stock trading strategy can ultimately be seen as collecting associated inputs, processing the data through an algorithm, providing a decision or likelihood for the available decision options a trader can make. This system is complex due to the large number of variables in a realistic environment. For the input there is range in sources of data from pure structured numeric, to unstructured biased resources such as word of mouth. Then there is the processing algorithm, be it a software mechanic that is rule based or machine intelligent systems that drive their own meaning. Finally, there is the desired output and the period of time for which the decision impacts. Should the trade be focused long term, short term, which markets? As a result of this complexity a range of techniques have been established from the simplistic manual evaluations such as technical indicators to the complex software processing function such as Neural Networks [6].

1.1 Technical Indicators

A more manual and simplistic way of predicting and making stock market decisions involves technical indicators [6]. Technical indicators attempt to simplify the stock market movement through iterative mathematical functions to drive insight from the movement of the stock. They are metrics designed to provide a high level detail on the stock movement. Unlike complex prediction or AI algorithms they do not predict exact price but rather direction or shape. Therefore, taking the followings structure seen in Eq. 3:

Let the stock price be:

$$P = \{P_1, P_2, P_3 \dots P_t\} \tag{1}$$

For trading from day 1 up to day *t* (the current day), the price can be the opening or closing price. The movement can be defined as the price difference between day t and some number of previous day ago, *k*, that is,

$$\Delta P_{t,k} = P_t - P_{t-k} \tag{2}$$

Technical Indicator Form

$$f(P, t) = indication\ of\ trend \tag{3}$$

Examples of such indicators are outlined by Vanstone and Finnie as they discuss consideration of gradient (Eq. 4), moving averages (Eq. 5), momentum (Eq. 6) (a more detailed moving average) and Moving Average Convergence Divergence (MACD) (Eq.7-11) (a metric that compares moving averages for 26, 12 and 9 days) [7].

Gradient

$$\frac{\Delta P_{t,k}}{k} \tag{4}$$

Moving Average

$$\frac{\sum_{n=t-k}^{t} P_n}{k} \tag{5}$$

Momentum

$$\left(\frac{P_t}{P_{t-k}} - 1\right) \times 100 \tag{6}$$

Moving Average Convergence Divergence (MACD)

$$MACD_{Line}: (EMA_{12\ day} - EMA_{26\ day}) \tag{7}$$

$$Signal\ Line: EMA_{9\ Day}\ (MACD_{Line}) \tag{8}$$

$$MACD_{Histogram}: MACD_{Line} - Signal\ Line \tag{9}$$

where,

$$EMA_n = \{Close - EMA_{previous\ day}\} \times multiplier + EMA_{previous\ day} \tag{10}$$

and,

$$Multiplier = \frac{2}{(n + 1)} \tag{11}$$

For first iteration EMA = Moving Average

1.2 Software Processing Functions

With the development and improvements within technology the cost of processing power has drastically decreased. As a direct result the systems have become easily available to the individual allowing for further research and improvements in all areas of data evaluation and analysis. This has been clear in the finance industry with the improvements and move towards cognitive processing systems and away from the rule based technical indicators for stock prediction. This has ranged from simple improvements and increased data size for regression and pattern algorithms, up to forms of Artificial Intelligence such as Neural Networks. However, their use has been limited to research and large scale organisations, very few options are available to the consumer, greatly disadvantaging potential investment options for an individual [8].

2 Neural Networks

2.1 History

Artificial Neural Networks (ANN) were first developed by Pitts and Mcculloch in 1943, designed as a mathematical model, describing the neurons interactions and individual logic function within an interconnected network, which they named MP Model. The model represented how a biological brain functions, seen in Figure 1. Their work led to a new area of research within computer science and engineering known as Neural Networks (NN) [9]. Since the creation of the model research into the area can be divided into three key stages. The first being the development of the model and its evaluation [10], being limited by the processing power and electronic circuit overlapping limit. With the development of more powerful and lower price points of personal computers NN research entered a golden age of research in the early 1980’s, being able to simulate neurons digitally rather than with hardware. This lead thousands of varying models and training techniques to be developed [11]. The final and current stage become clear in the early 2000’s as NN models began to be tested and developed for practical applications, from pattern recognition [12], decision making, and prediction, being utilized in a range of industries from agriculture [13], to medical community [14] and economic management [15].

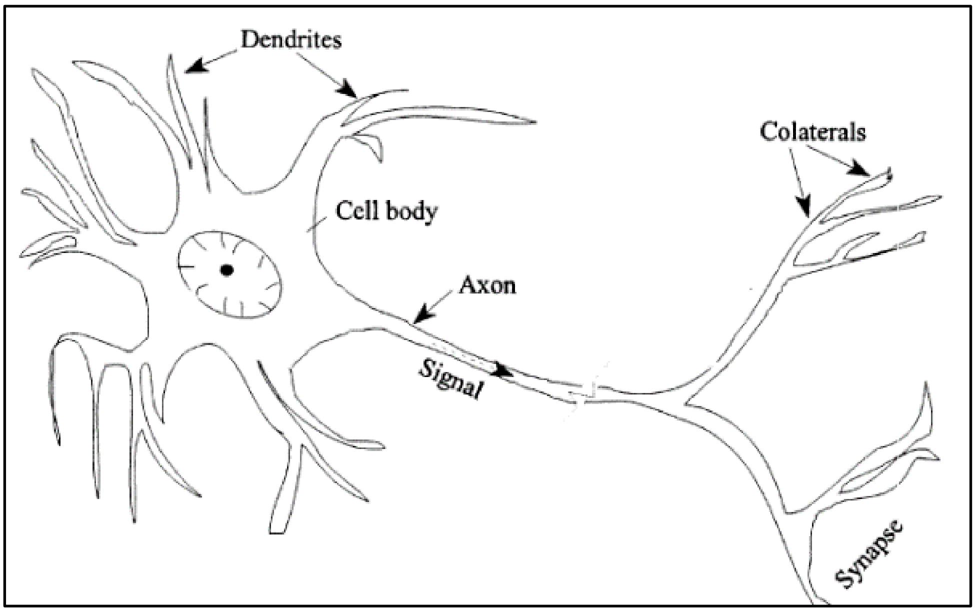


Figure 1. Schematic of biological neuron. [17]

2.2 Neural Network Function

2.2.1 Basic Model

ANNs are a computational tool that creates non-linear functions to fit a data set, allowing for future predictions or outputs on unseen data [16]. The model is loosely based on the function of a biological brain (Figure 1), [17]. In the brain a neuron consists of a cell with an axon. Two neighbouring neurons can communicate through their axons by sending a surge of energy across the synapse [17]. In the brain there are a series of neurons loosely connected through synapses, lots of incoming signals reach the neurons but it is only when a signal reaches a certain strength that the neuron is fired and an electrical signal crosses the synapse. Ideally in an ANN each neuron is represented by a tiny CPU which accepts input and only outputs a 1 if the strength of the incoming signal is strong enough. Input can be from sensors, alternatively the tiny CPUs can accept input from another CPUs in the same network. At the other end of the network, the role of the CPU is to produce output which is directed to actuators. The tiny CPUs need to have sufficient 'intelligence' to only output at '1' (to either the next neuron in the hidden layer or though the output device) if the input is 'strong enough', exceeding the threshold. It determines the strength of the input by multiplying the strength of each signal by a determined weighting. If the sum of the inputs is greater than the threshold value, the neuron outputs '1', see Figure 2. By

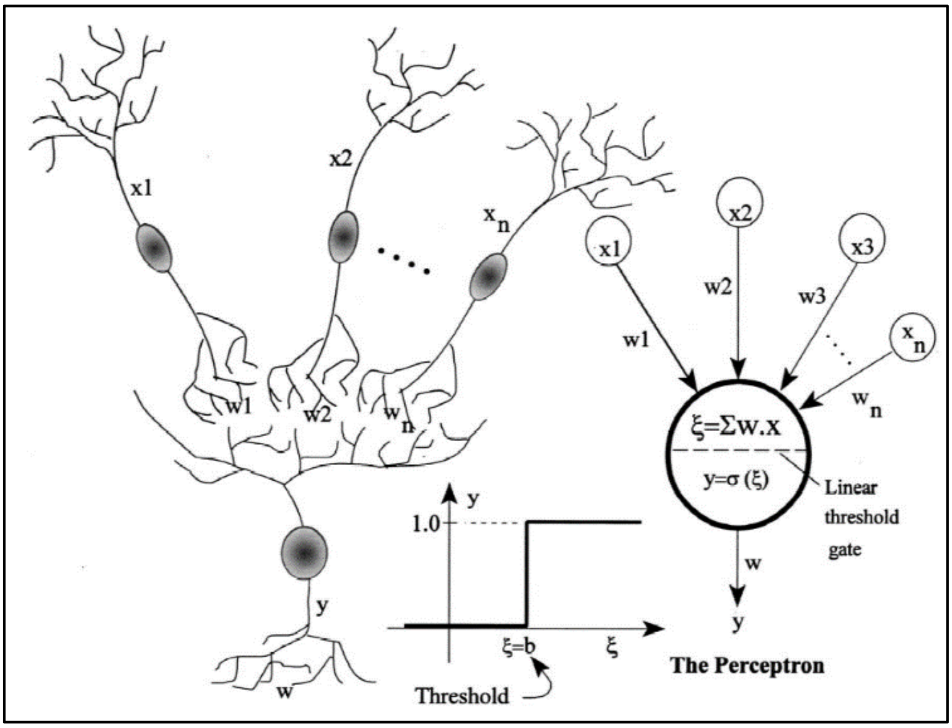


Figure 2. Interaction of neurons, depicting the similarity between biological and digital neurons. The summing of signals is also depicted. [17]

changing the weightings, we can dramatically change the output of the whole NN system. A complete ANN consists of layers of these neurons connected together where the output of one neurone becomes the input of the next. With the improvements in software neurons are no longer represented by CPU but rather programmatically in software. This has allowed for a huge decrease in price and increase in availability of the technology. The general NN model is broken down into three layers (Figure 3). The first is the input layer in which the known values are entered. This enters a hidden layer, of a set number of neurons. The data flows through, finally, to the output layer in which the expected value is output [18].

The functioning of a NN is split into two stages.The first is the Training Cycle. One method of training is known as supervised learning. For this technique a NN is exposed to a series of situations in which the answer is known. If the NN output is inappropriate or inaccurate, the error from the expected value is used to adjust all weightings and thresholds so that this and all other responses are correct or at least closer to correct. The second technique is unsupervised learning. For this method the network is exposed to a huge dataset with unknown answers, the network therefore draws its own conclusions. This method is usually used for image identification. For example one could feed a network thousands of images. The network ideally establishs its own catagories of houses, scenery, cats or others, based on what it believes. To train a NN adequately, it is essential to expose it to as many known situations as possible [19]. The second phase is the Execution Cycle. Once the NN has been sufficiently trained, values can be input for a situation to which the answer is unknown. The output is based on the weightings and thresholds, which were developed during the training cycle to consistently output the answer. The answer is therefore based on experience, just like for a human. At this point one has no choice but to accept the answer on the output value, just as one would from a human expert. Currently there is no way of asking the system to justify its response.

A NN is perfect for pattern matching, can establish non-linear functions and does not require knoweldge or facts. Simply requiring some input values, it can therefore be created with relative ease, particularly within software packages such as Matlab. However a NN is limited as it can often be difficult to interpret the results and there is no explaination of how the result was reached. Furthermore, due to the limitations of hardware it became difficult to improve the system and thus software solutions were developed. However with increased numbers of neuron calucations and weighting the processing requirement increases exponentially putting large stress on computational processing power [20].

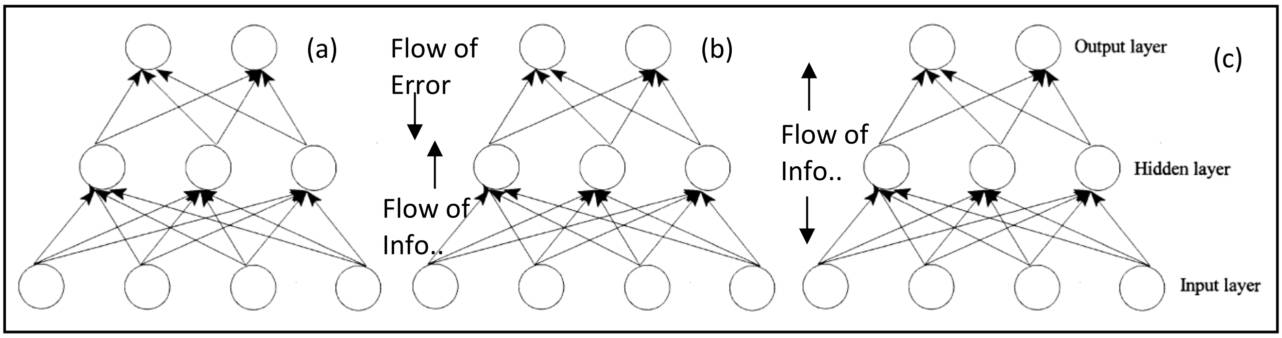


Figure 3. Three layers of a NN. (a) Feed Forward model, (b) Backward Propagating, (c) Recurrent/ Time Series [17]

Simplified Neural Network Elements

where the input layer is defined as:

$$X_i, i = 1,2,3 \ldots \tag{12}$$

The hidden layer is a weighted sum of the inputs. The output of the hidden layer is:

$$h_j = \sum w_i X_i \tag{13}$$

where w_i are the weights. The inputs to the output nodes is also a weighted sum, that is:

$$g_k = \sum Z_k h_k \tag{14}$$

2.2.2 Models

With years of research, and reference to a variety of problems a range of different NN models have been developed, each with their own unique nuances. Three of the most common and overarching models are;

2.2.2.1 Feed Forward

Simply takes input and flows through each neuron without having connection between previously utilised neurons, therefore creating an only forward flowing chain of information (Figure 3a).

2.2.2.2 Backward Propagating

Is the most widely used type of NN [17]. It is similar to the Feed Forward model, however differentiates itself with how it handles errors. Rather than simply evaluating the error difference between the input and output layer the error is also fed back through each of the hidden layers, evaluating the error at each step for the training process, impacting the applied weighting. This allows for increased evaluation of the network (Figure 3b).

Backward Propagating

$$w \rightarrow E(f_n(w,x),y) \tag{15}$$

where:

$$E(y,y') = |y - y'|^2 \tag{16}$$

2.2.2.3 Recurrent or Time Series

Unlike the aforementioned models that only focus on a forward flow of actual information, this model utilises a more cyclic system. Outputs of some neurons are fed back to the same neurons or preceding layers. This allows for a more dynamic model as it adjusts to changes and can be utilised for time series data such as stock market movements (Figure 4).

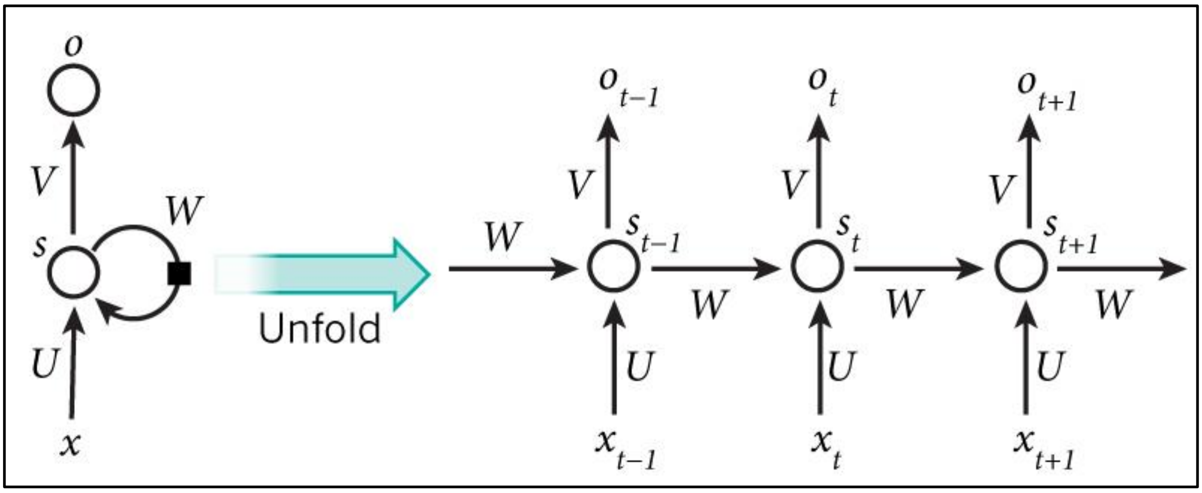


Figure 4. Diagram of Recurrent Neural Network, where x is input, o output and s is a hidden state [39]

The elements of Figure 4 can be expressed in the following:

$$s_t = f(Ux_t + Ws_{t-1}) \tag{17}$$

$$o_t = g(Vs_t) \tag{18}$$

Functions f and g, are chosen depending on the intended purpose of the system. It is important to note that *U*, *V*, *W* are not the same value per iteration and are constantly changing.

3 Application of Neural Networks in Finance

The immense size, diversity and potential of wealth associated with stock market prediction and trading methodologies has resulted in huge growth in the research area. This is evident in the diversity of research topics in ANN application in the prediction of stock markets. There is research in defining a clear methodology for developing such a system, comparison of different network models, index and exchange rate prediction, valuation of different input/output indicators, trading strategy evaluation and a range of benchmarking techniques to evaluate the system. The articles can be evaluated and analysed by addressing their main intention; defining a methodology, direct price prediction, trading strategy implementation and evaluation or a combination to produce a full-fledged system.

3.1 Market Price Prediction

The ultimate idea around utilising stock market data with NNs is to predict the future of the stock. There are two ways to approach this, to predict what the trader should do in the future, as outlined in section 2, or simply to predict the price movement. By being able to predict the price movement more accurately ideally this will lead to better, more actuate data, thus the decisions made using this output will too be more accurate. Active stock market prediction has been

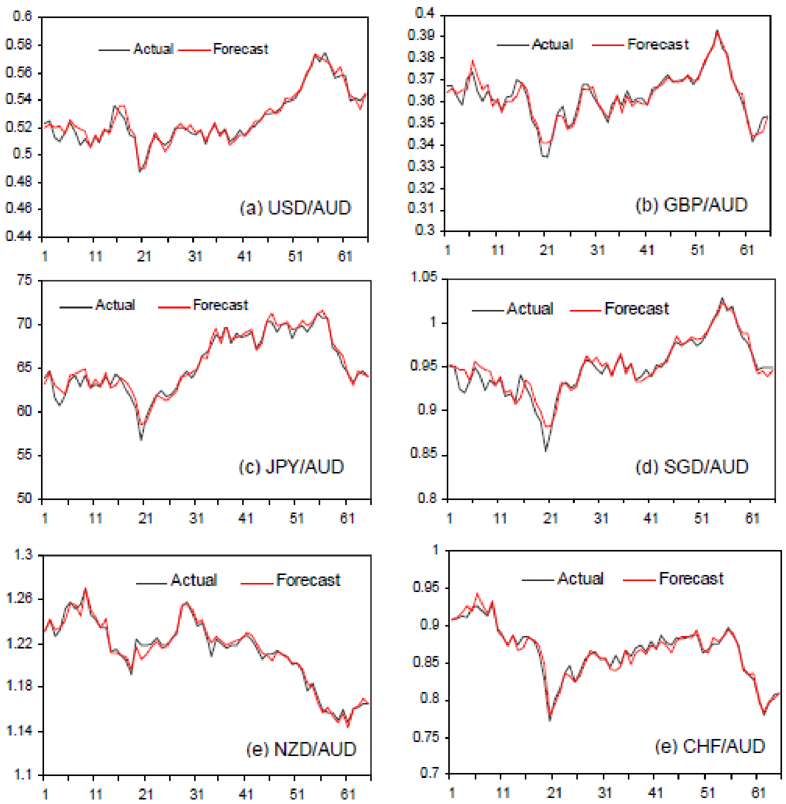


Figure 5. Forecast currency exchange by SCG based NN for 65 weeks. [21]

present in research since the beginning of the Millennium. However, the diversity in parameters is huge, analysis different models, network nodes, inputs, outputs, stocks, indices most using different measures of performance, evaluating accuracy, error and different time samples. As a result, it has become difficult to address the best performance or best system.

The early 2004 paper, Forecasting of Currency Exchange Rates Using ANN by Kamruzzaman and Sarke, was one of the first papers to utilise the theoretical knowledge of NNs on a practical, realistic market [21]. The paper outlined the high level of accuracy possible within exchange rate prediction for SBP, SCG and BPR NN models. With the SCG model ultimately performing the best. Figure 5 displays their results for currency exchange over 65 weeks. It is clear that the forecast value follows closely to the actual value. Due to the limited computing power at the time the models were only evaluated for 35 weeks and 65 weeks [21]. Their performance was evaluated on a range of error evaluation criteria. This document produced a pivotal result as it was an early indication of the potential of NNs within the financial industry.

When predicting the movement of Australian Stock Index in 2005, Pan, Tilakaratne and Yearwood were able to produce a maximum 80% accuracy on whether the stock price for the following day would increase or decrease [22]. They were able to achieve this by utilising a Multi-Layer Feed-Forward NN from the time series data of five other Indexes; opening, closing, high and low price. Although they were able to achieve such high accuracy the practical considerations, potential profit or trading decisions were not considered.

In the following years a range of research was done using Indexes and Exchange rates, however, in 2009, Kozdraj evaluated 30 actual stocks using a feedforward NN model. In the paper the number of neurons and layers is evaluated and outlined as a crucial factor impacting the networks performance. No ideal numbers are indicated as Kozdraj outlines “there is no direct rule allowing to get the optimum number of iteration and parameter settings” [23]. The error within all stocks ranged drastically and the author outlines that for stock price a universal forecasting method does not exist.

The pessimism of Kozdraj in the potential of NNs as a universal stock market forecasting model is questioned in the 2014 paper by Shah, Prabhu and Rao in which they evaluate three models; Multilayer feedforward, Recurrent and Radial basis prediction ability of NNs on five stock market data sets [24]. All models are able to produce an accuracy of over 80% with a maximum of 94.9%. They were able to produce such high accuracy using technical indicators such as rate of change and momentum. Their models were only evaluated over a 500-day time period and did not consider the practical or possible commercial potential of such research.

Kara, Boyacioglu and Baykan compared Support Vector Machines and NNs in the prediction of direction potential of each model when given 10 technical indicators [25]. Their models revolved around the prediction of the Istanbul Stock Exchange price index. They hypothesised due to the size of noise within stock market data the SVM machine would perform better. However, it was found that the NN performed better with a 75.74% accuracy compared to 71.52%. Their research outlines NNs potential in prediction, however, again similar to the other papers discussed, the practical nature of the research is not addressed and the use for such a system is not discussed.

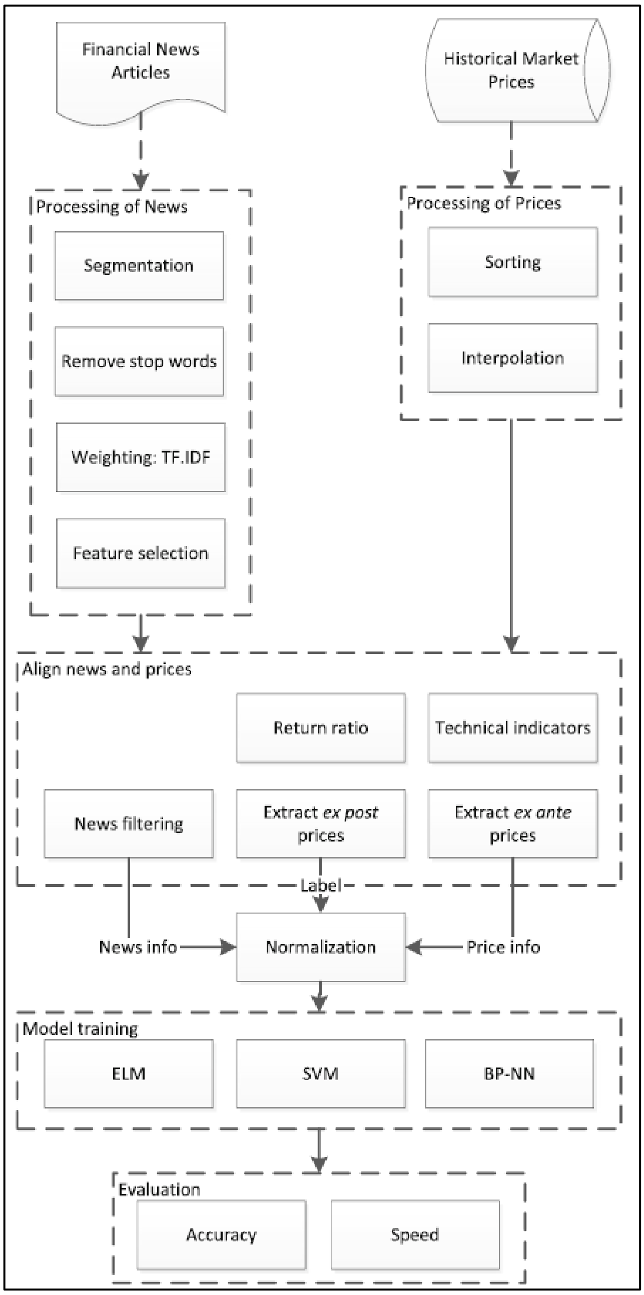


Figure 6. Architecture of trading signal platform. [27]

Ganhe and Chaudhari in early 2016 compared stock market prediction techniques; NN Time Series Models, Regression analysis, Support Vector Machine and Adaptive Linear Combiner and Artificial Bee Colony Algorithm. Their report addressed the concerns and advantages of each model. Their article is differentiated as they are not solely focused on accuracy but rather, performance as a whole and have no interest in the actual practical application. Their findings outlined a true benefit in using NN Time Series due to their greater performance than regression models and lower prediction error. Yet one must consider the impact of noise on the model [26]. It is evident that NN prediction is a formidable method of stock prediction. This article illustrates the importance and value of developing a stock prediction system utilising such a model.

With the increase in computational power and potential for analysis and flow of data, in 2014, Li et al. were able to build a system that utilised not only stock price data but also news articles to predict the movement in stock prices. Their detailed system block diagram is depicted in Figure 6. The evaluation of the system focused on the comparison between error in three models; Extreme Learning Machine, Single-Hidden Layer Feedforward Network and Back-Propagation Neural Networks. They noticed that the ELM required much larger CPU resources, yet the Feedforward Network was able to produce the highest accuracy in prediction [27]. Their system although complex, well built and strong in nature did not perform much better than other models and it appears the increase in complexity was not worth the trade-off. Furthermore, their evaluation was based solely on accuracy, omitting its future in a financial industry.

In the early 2010's a range of research continuing on evaluating the accuracy of NN prediction, comparing models, number of nodes and layers and different stocks. Kar was able to achieve an average accuracy of 88% [28], in a range of experiments run with a differing model paradigms. This outlines that although there is a huge range in network settings, ultimately the prediction is still rather high and accurate, outlining its potential within a commercial environment and economic benefit. This is furthered by the 2015 article by Falat and Pancikova in which they compare seven different NN models all of which have a mean square error of below 0.0001 [29]. Vika, Sevrani and Vika had the similar findings when comparing two NN models having a maximum mean error of 0.0115 [30].

The 2015 report from Millevik and Wang truly reiterates the potential of NN prediction, as they address the potential of a Multilayer Feedforward Neural Networks in prediction. Unlike the other reports their evaluation is on training, validation and testing breakdowns. Their results, regardless of breakdown, lead to an accuracy greater than 97% [31]. These articles all contradict the belief of Kozdraj, that a universal stock market prediction model could not exist, as the research indicates a large number of models exist that convey true potential in prediction. From the aforementioned research it is clear that there is no clear best network setup, training procedure or data input, rather it outlines the diversity and true dynamic nature of NNs in prediction.

Jabbarzadeh et al. evaluate the S&P 500 Index using seven technical indicators; moving average, momentum, relative strength index, price channel index, moving average, convergence divergence and random fluctuations as inputs to predict the stocks movement. The technical indicators require a large amount of pre-processing to ensure valid input to the NN. To evaluate the performance of the system they interpret error values, rather than addressing accuracy [32]. Their values are comparable to other models mentioned and thus outline that increased processing power required for pre-processing does not lead to a more accurate result. It is thus evident that when implementing such a NN model with current technology it is best to use simple inputs, if the increase in accuracy is not essential.

The discussed articles so far have focused on either predicting the movement of a stock or the actual price. The 2016 paper by Liao, approaches the potential of networks differently and focuses on being able to predict or consider the risk of a stock price crash. This is an area which previously had not been considered in research. A feedforward neural network was used to evaluate if the stock was going to crash, or not, on a daily basis. Unfortunately, the results were not particularly positive as the model was only about 2% more accurate than random prediction and about 1% more accurate than a logistic model [33]. This model was limited as only data from one stock was used, whereas in reality a large or notable crash is rarely from a single source, rather a cascading effect seen throughout the market.

Shynkevich et al. attempt stock prediction in a completely different manner than the methods outlined as they utilise different categories of news articles. Their system categorises news data running textual data pre-processing. This is combined with historical stock data to predict stock movement. The model produced the best accuracy of 82.4% [34]. It is clear again that complexity in the model does not increase performance

Manikandan and Subha evaluate the potential in wizard/ui NN applications within Matlab. The articles address the Nonlinear Autoregressive with external inputs (NARX) model in predicting the next day price of five different currencies producing 90-95% accuracy [1]. The findings outline the potential in using NN function in Matlab for stock prediction, however does not go further, only evaluating its accuracy.

From the above discussion the diversity in research is clear, yet some clear insights can be drawn. All models regardless of complexity, paradigms, network structure have been able to produce models that are of reasonable performance, usually giving better than 80% accuracy, an indication that NNs have strong prediction potential in stock markets. The main focus of research has been on indices and exchange rates; little consideration has been made on individual stocks. The shape or movement classification of stocks has also not been addressed. However, the most evident issue is the lack of consideration for the practical application of such a system, rarely considering its profitability of commercial function, despite its clear success and accuracy in prediction.

3.2 Trading Strategy Evaluation and Implementation

Most of the aforementioned models had little to no consideration of how the predicted price could be utilised in trading decisions or profit evaluation, simply focusing on how accurate the predicted value could be. For the business application of a NN trading system it would be essential to be profitable and be able to make decisions. The prediction is thus a cog within the trading machine. A range of trading techniques have been developed, however rather than focusing on predicting the movement the following day they address the current day and evaluate how good a decision it would be to buy, sell or hold the share on that current day.

The paper by Tilakaratne et al. is an early example of trading strategy on predicting the best choice rather than the actual movement of the price. Their paper focuses on a handful of indexes that ran a trading simulation of 78 days, a sample period most academics would consider too small. Their technique utilised a NN to output likelihood for buy, sell or hold signals. Their system was able to produce at best 10% rate of return, only marginally beating the control systems 5.6% [2]. The paper simply counted trade signals and did not evaluate if they were good or bad decisions and the system did not consider commission, a cost that is hard to avoid in reality.

The 2016 paper by Schulze-Roebbecke, focused on trading of crude oil, copper and gold on the futures market. The trading technique used within their system was more complex, and evaluated markets for 15 years of data. Their technique utilised NN of a feed-forward model. The system was able to produce a minimum of 8% annual return and maximum 15%. Again however commission was not considered. Improving on the aforementioned paper the trading signals decisions were evaluated, ranging from 47% to 57% of trades were the correct decision [35]. Although they a successful trading system was developed that could produce consistent return annually the practical applications were not considered.

A more complex trading model is developed by Dymova, Sevastjanov and Kaczmarek in their 2016 paper which evaluates trading on the currency exchange market. The system moves away from a rule based trading method, utilising fuzzy logic to develop weightings and NNs to produce a buy, sell or trade signal. Unlike the other papers discussed the model trades in 15mins, 30mins, 1hr and 4hrs increments rather than daily providing a much larger data set. The system produced maximum ROI of 161% usually for small time interval trades. The success of the trading system was also evaluated on the percentage of correct decisions ranging from 45-61%. The stock evaluated is only those that have increased over time, the system was not attempted on decreasing stock and does thus does not address a realistic market or commercial system. Furthermore, commission is not considered and thus impacts on its practical usage.

The aforementioned articles were all able to produce a profitable system that is able to indicate the correct trade signal about 50% of the time, however the average profit or loss of the decisions were not considered. The systems did not include commission and no practical usage or evaluation of the system was considered.

3.3 Hybrid Systems

The above outlines the division between stock prediction and trading decisions, there is therefore the importance of combining the two to create a system that can be evaluated on its profits, decision choices and accuracy, to have a practical and commercially beneficial system. Progress in this area has only recently begun with a few articles attempting to address this issue.

The 2015 Masters Thesis by Aamodt builds a system that trades stock comparing six models; Support Vector Regression Feed Forward Neural Network, Echo State Network, Conditional Restricted Boltzmann Machine, Time-Delay Neural Network and Convolutional Neural Networks on the amount of profit each model drives. Aamodt does not outline the trading technique used, however, it is known that commission is not considered in the profit calculations. The model was run for a period of 3 years receiving a maximum profit of 30%, therefore 10% annually. The model by Aamodt is well structured using a range of stocks for evaluation, each with a unique movement, some displaying loss over time. It is concluded that the Feed Forward Neural Network is “most viable for trading” [3]. The system established is practical and functional however the profit is not much higher than investment in a high interest rate bank account and does not include commission costs.

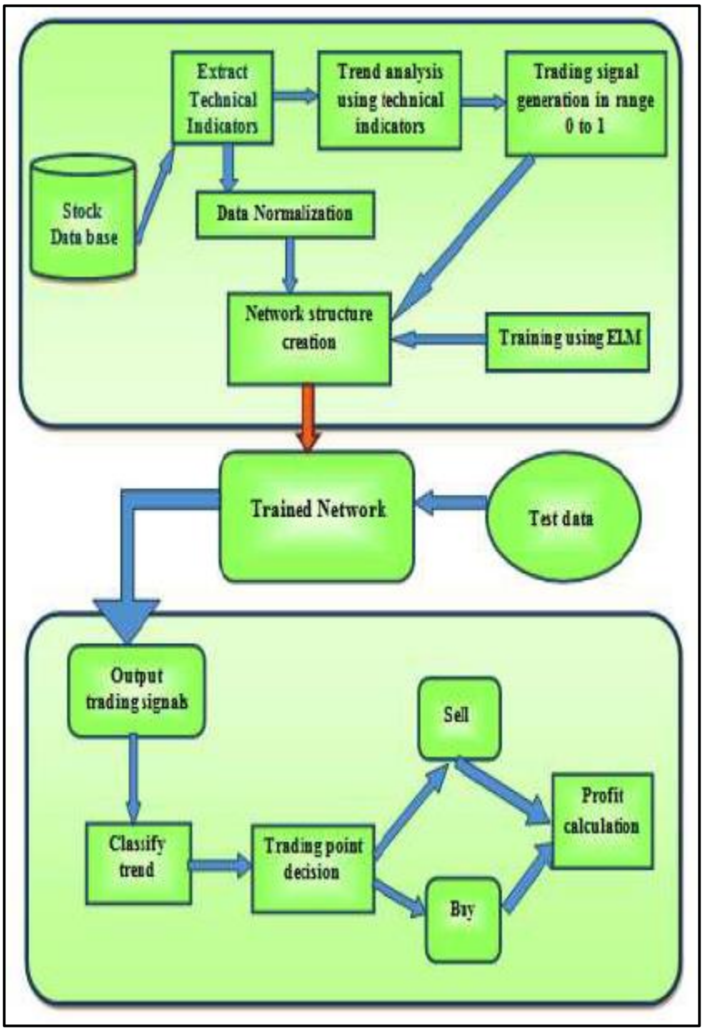


Figure 7. Proposed Model for Stock Trading. [36]

The 2016 paper by Dash, and Dash, creates a trading model that implements a strong prediction and decision unit, to make well calculated trades. The system uses the structure seen in Figure 7. Their system, unlike any others, discussed focus on a longer term trend to make trading decisions. This is achieved by utilising technical indicators to address the trend of the stock, this is then fed into a NN, that combined with the history of the stock is able to make appropriate decisions. This model trades less regularly and thus would be more reasonable in an environment that includes commission. The model on the BSE SENSEX data set has an annual profit of 47% and 24% on S&P500 [36]. This model trades rarely and focuses on larger payoffs, although this reduces the impact of commission it also increases the risk associated. The system also only tested indexes rather than individual stocks and thus would behave differently in a real stock market. Only increasing stocks, with one crash is considered thus the data set is limited.

The stock trading system designed by Chiang et al. is the best performing and well tested system that has been documented. Their model has been evaluated on 22 stocks, all ranging in form and price bracket. Their system architecture is depicted in Figure 8. The system is also the best performing, making maximum profit of 71.08% and minimum of 24.05% per annum. This outperformed the previously mentioned system and this is for longer term trades. Its short term method of trading has returns of 103.79% [5]. However, neither evaluation includes commission. Ultimately this is a strong, well performing and dynamic model, but for true evaluation it is important to evaluate the number of trades and whether the decisions were good or bad and this system has not been evaluated on these criteria.

It is evident that it is possible to build a model that utilises NN prediction to produce stock price movement and trading strategy that is potentially profitable. However, consideration for commission or implementation within an environment where commission could be bypassed is essential to bring this model to the commercial environment. Furthermore, to ensure valuation of risk and viability it is crucial to not only validate the model on profit but to also test it rigorously with different stock, and criteria.

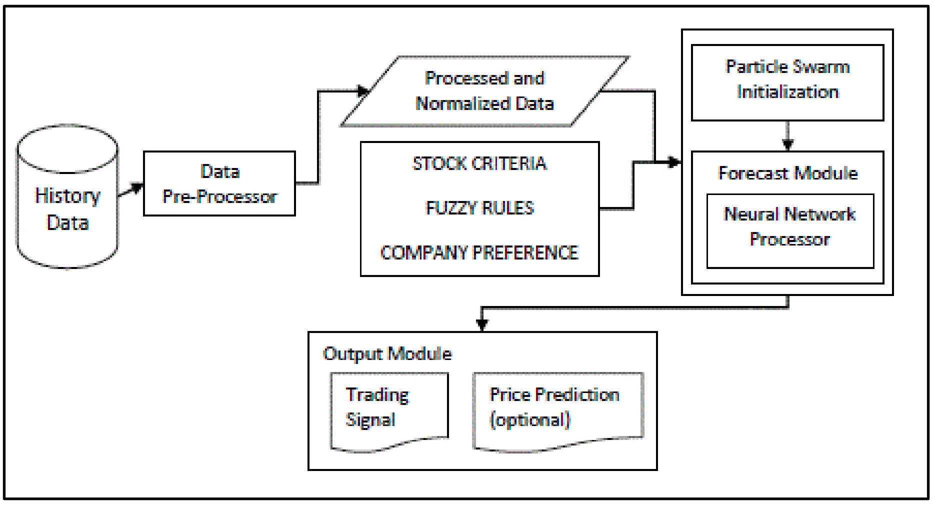


Figure 8. Implemented Model. [5]

3.4 Design, Implementation and Evaluation of Neural Network Trading System

In 1996 in the early stages of NN application research Kaastra and Boyd established a clear and well-structured methodology for developing a stock market prediction system that utilises NNs. Their article outlined eight steps for producing a forecasting model; variable selection, data collection, data pre-processing, training, testing and validation sets, NN paradigms, evaluation criteria, network trading and implementation [37]. The methodology is well designed as it is independent of model, the document however, does not consider further stages simply focusing on prediction of price, use of such a system is not discussed. Furthermore, its evaluation discussion is limited as it can only focus on how accurate the prediction is, rather than how useful the system may be.

Vanstone and Finnie build upon the methodology established in 1996 and they outline considerations for the topics missed in the earlier Kaastra and Boyds structure. The article addresses concern of a more accurate representation of a real trading environment, emphasising the impact of commission and slippage. It values the importance of economic theories for valuing stock and includes these attributes in the development strategy, discussing the importance of moving average and momentum in stock movement. A clear outline for the trading system is given emphasising the importance of including three major functions; rules to enter and exit trades, risk control and money management [7]. Their final discussion revolves around metric measurements, outlining the limit in simply valuing profitability, as it does not convey the risk, capital requirements, or consistency. To resolve the issue a range of new measurements are suggested to gain a better understanding of the developed system and its performance, seen below. Although this improved methodology addresses concerns of the previous structure it does not value or address different NN models and their potential, nor outlining what trading strategies are considered ideal. It is thus essential to evaluate prediction models and trading strategies.

Net Profit: Ending Capital – Starting Capital

$$Captial_t - Capital_1 \tag{19}$$

Annual Profit (%): Annualized Net Profit (Loss). Also known as Annual Percentage Return (APR)

$$\left(\frac{\left(\frac{Captial_t - Capital_1}{Capital_1}\right) \times 100}{k}\right) \times 365 \tag{20}$$

Number of Trades: Total Trades initiated by strategy

$$count(trade) \tag{21}$$

Winning Trades (%): Percentage of trades that were winners

$$\frac{count(positive\ trade)}{count(trade)} \tag{22}$$

Average Profit: Average profit per winning trade, expressed as a percentage. Includes effect of trading costs, and does not take open positions into account

$$\frac{sum(positive\ trade)}{count(positive\ trade)} \tag{23}$$

Losing Trades (%): Percentage of trades that were losers.

$$\frac{count(negative\ trade)}{count(trade)} \tag{24}$$

Average Loss: Average loss per losing trade, expressed as a percentage. Includes effect of trading costs and does not take open positions into account.

$$\frac{sum(negative\ trade)}{count(negative\ trade)} \tag{25}$$

Max Drawdown (%): Largest peak to valley decline in the equity curve, on a closing price basis, expressed as a percentage of open equity.

$$Max\left(\left(\frac{Equity_{close} - Equity_{open}}{Equity_{open}}\right) \times 100\right) \tag{26}$$

Profit Factor: Gross Profit divided by Gross Loss (Desirable systems should display over 2 for this ratio)

$$\frac{Gross\ Profit}{Gross\ Loss} \tag{27}$$

4 Summary

The detailed analysis of the aforementioned articles outlines NNs ability to predict stock market price movement and the success of other researchers in implementing such models. From the research it is clear that a range of models are able to produce solid output and thus are viable in producing a profitable and functional trading model. Further research supports the capability of Matlab to do so. It is clear that all system evaluation methods have been limited, focusing rarely on profit, rather on accuracy, never truly evaluating good/bad trades. It is clear therefore that a system built in a realistic trading environment that considers commission, slippage, evaluating decision making based on NNs and finally evaluating a ranch of metrics, would be a beneficial piece of work. There is also the potential, if developed correctly, for the system to be implemented within a real world environment, enabling large profit and establishing commercial, economic and social value. Based on an analysis of past research the current piece of work clearly outlines that such an endeavour would be unique and add to a range of industries. This outlines the importance and impact of such a thesis project. Unlike some of the aforementioned systems a step forward, recurrent network approach will be used.

Chapter 3: Methodology

To ensure accuracy and replicability a well-structured methodology is described in this chapter. The inputs, outputs and structural elements are all outlined in detail to ensure a clear definition of the system, allowing for others to replicate the research within Matlab or another application; testing a range of inputs, whilst utilising the same evaluation methods. By doing so the research can be verified and validated.

Section 1 and Section 2 are two system diagrams that gives an outline of how the trading platform functions and how an accurate simulation is performed, discussing the application in which it is built and the functions used. The following section goes into details of the function and elements that make up the program, outlining the process within each and what is performed. Section 3, amalgamates the previous section describing the full function in plain English allowing for replication in future within any application. Section 4 and 5 look into the parameters of program. Section 4 discusses the trading strategies that were evaluated and Section 5 looks at the stock that were used. The chapter concludes by addressing the limitations and errors of the body of work and how they were addressed.

1 System Diagrams

1.1 Stock Evaluation Diagram

The constructed system addressed most of the concerns and missed evaluation outlined in the literature review. The trading environment was built in Matlab, a multi-paradigm numerical computing environment. It was broken down into three main sections. The predictive stage undertaken by the NN, the decision stage executed by the trading strategy and finally valuation/benchmarking which was used to evaluate a large number of indicators conveying the performance of the model (see Chapter 4 and 5). These stages are shown in the block diagram outlined in Figure 9. Due to the large number of variables and possible set ups the system was designed to allow for easy change of stock input, NN model and trading strategies. The following selection options were used:

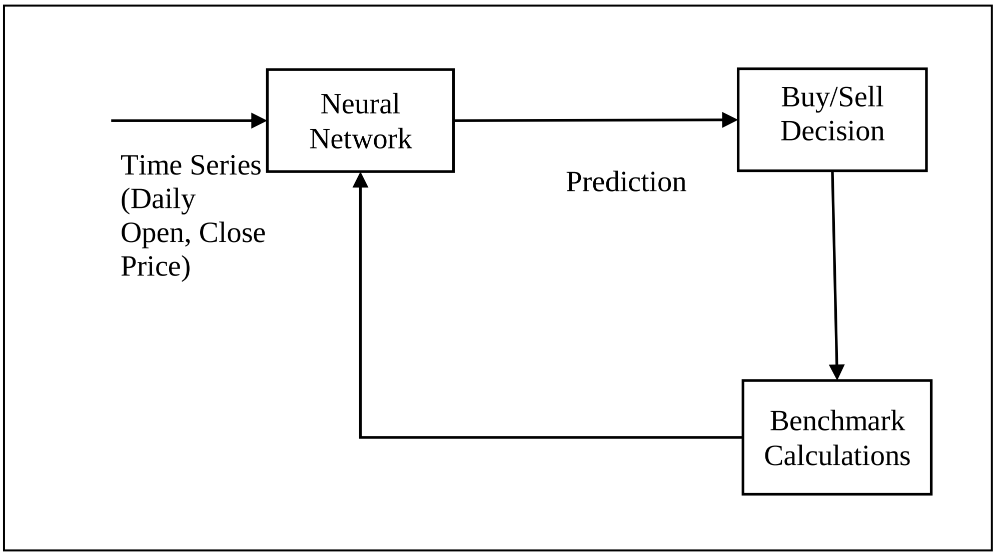


Figure 9. System Diagram

1.2 Full System Diagram

Figure 9, depicts how a single stock is evaluated, however for the purposes of this research 10 strategies were required to be tested, each on the 22 stocks that were selected. As a result, it was not feasible to do so individually. To resolve this issue, increase efficiency and allow for repeatability and accuracy, a three-tiered looping system was designed. Figure 10 is the diagram of this system. The first loop chooses the trading strategy, the second selects the stock, with the final loop running the simulation. Therefore, each method is evaluated on every stock, this process is described further in Section 4: Pseudo Code Description.

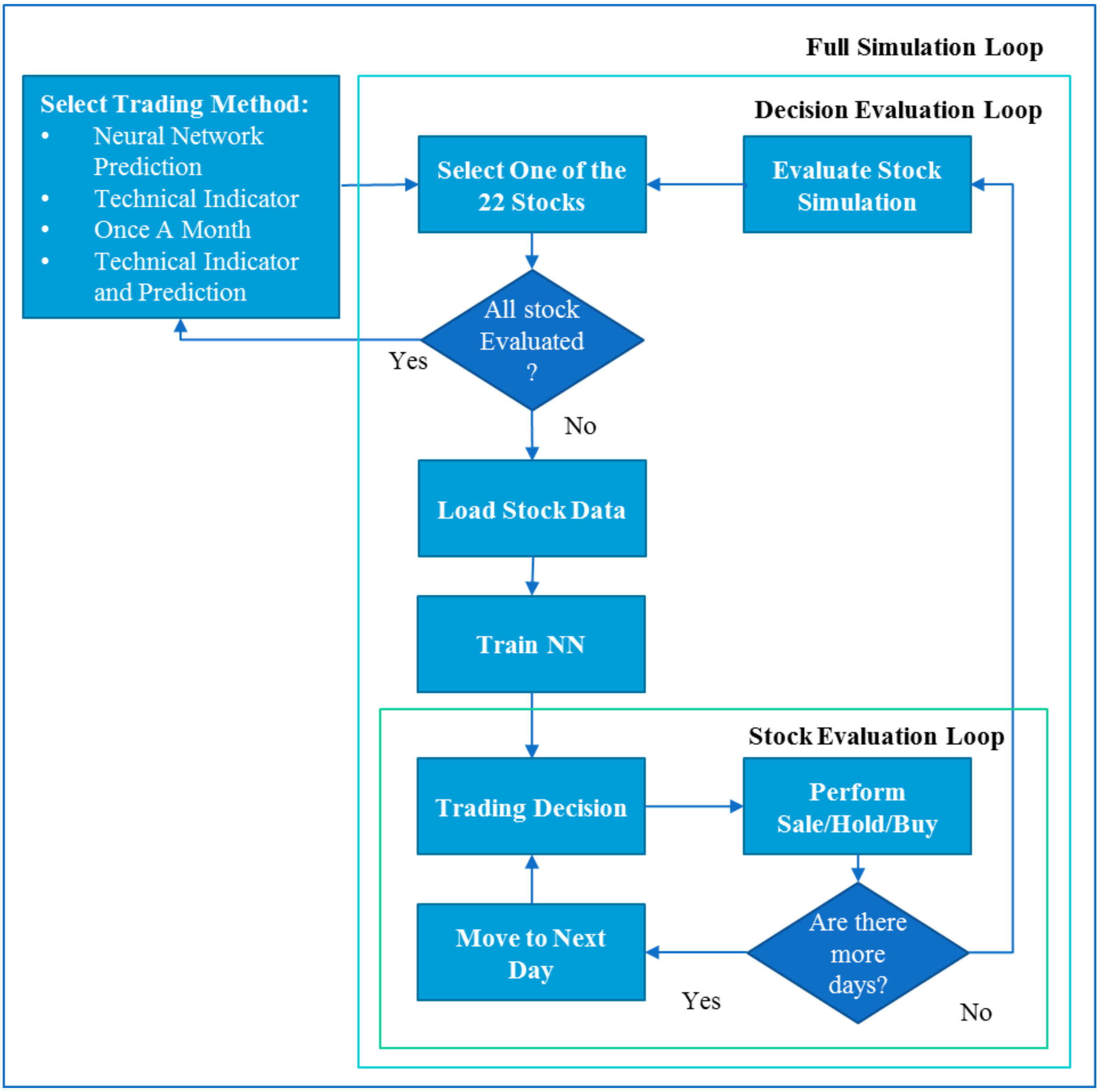


Figure 10. Full Testing System Diagram

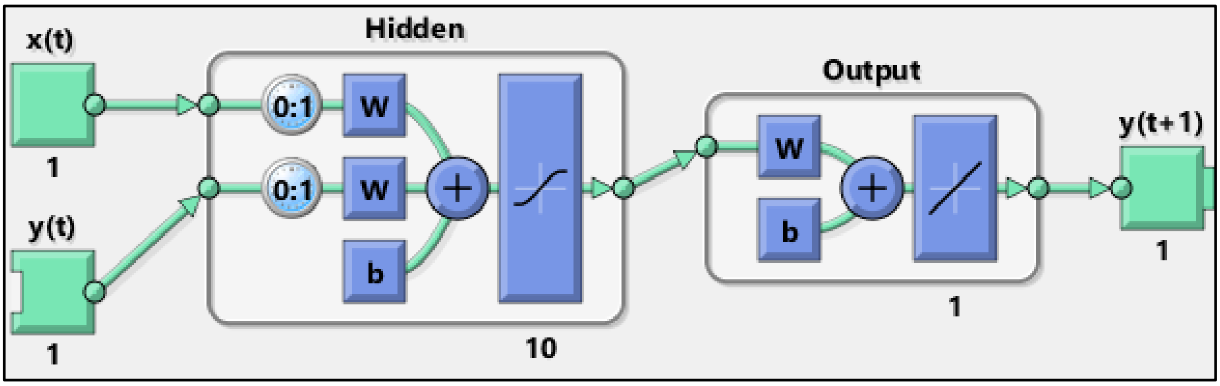


Figure 11. Matlab NARX NN Model used for one step ahead prediction

- Input Stock:
  - Constant Increasing
  - Constant Decreasing
  - Constant
  - Sudden Increase
  - Sudden Decrease
  - Erratic
- Neural Network Models:
  - Time Series, Nonlinear Autoregressive with External (Exogenous) Input (NARX) Step-Ahead Prediction (Figure 11). Outputting the following days closing price
- Trading Strategies (further analysis in section 5):
  - Simple: Buy (If going to increase), Hold, Sell (If going to decrease)
  - Logic:

$$if\ P_{closing,t+1\ (prediction)} > P_{closing,t}\ then\ buy\ when\ possible$$
$$elif\ P_{closing,t+1\ (prediction)} < P_{closing,t}\ then\ sell\ when\ possible$$

  - Complex: Consider size of predicted increase or decrease and its impact, use technical indicators (TI)
  - Logic:

$$if\ \left(P_{closing,t+1\ (prediction)} > P_{closing,t}\ \&\ given\ TI\ indicats\ growth\right)\ then\ buy\ when\ possible$$
$$elif\ \left(P_{closing,t+1\ (prediction)} > P_{closing,t}\ \&\ given\ TI\ indicats\ decline\right)\ then\ sell\ when\ possible$$

2 Code Functions

2.1 Model

This is the main function of the program. The function accepts four inputs. Selection on which stock is to be simulated, the trading method used, the initial investment amount and the commission value used within the simulation. Within this function time cycles (each day of the simulation) are run, graphical outputs are displayed and the following functions are called.

2.2 LoadData

From this function one can easily choose the stock they would like to simulate from a selection of excel documents exported from Google Finance. The function imports opening, closing, high and low price as well as volume for each associated date. This is stored within a table for easy access by other functions.

2.3 TrainNN

This function takes an input of the chosen information on the stocks (OPEN/CLOSE Price). This function trains the network using Levenberg-Marquardt backpropagation (LM) [27], with 10 hidden layers. A step-a-head neural network is produced and returned to the main to allow for predictions to be used in simulation and decision making.

2.4 Trading Signal

This function will take in the trained NN, the selected trading method, a matrix tracking stock ownership and a count value. It will evaluate if stock can be purchased or sold, evaluate what is predicted to occur and decided on the best trading decision to be made. It will simply output a 1 to purchase stock, a -1 to sell or a 0 to hold the stock.

2.5 Market Simulation

The core function that simulates market sales and purchase of shares. It tracks and facilitates the trades, including commission if specified. It will also prevent a transaction if a stock is already purchased or capital is not available.

2.6 Control Investment

To evaluate how successful a trading function has been a control point of bank account investment is calculated within this function. It pulls the historical data of the RBA official cash rate and evaluates an equal invest if placed in a bank account over the trading period to address if it was better to invest within this trading system or to leave the investment in a bank account.

2.7 Benchmarking

This function allows for the evaluation of the system. Once the simulation has been run this function is called to calculate a range of indicators of the performance of the system. The following values are calculated;

- Net profit – the total profit at the end of the simulation
- Percent profit on initial investment – the percentage change from the initial investment normalising the result
- Annual profit – percent profit divided by the number of years the simulation ran for
- Number of trades – the total number of trades that occurred during the simulation
- percent of good/bad trades and their average loss/gain – evaluates if the trade was profitable or resulted in a loss, the number of instances is counted and average of the impact found

These metrics were chosen based off the methodology by Vanstone and Finnie [7] and all formulas are outlined in Chapter 2, Section 3.4.

3 Training Method

LM was chosen as the training method as it is the fastest, and is recommended as a first-choice supervised algorithm by MathWorks [33]. Speed was essential as a large number of simulations were run. The drawback of the training method is the large memory requirement, however the system was run on a high grade machine of 8 GB RAM, by doing so the performance was not impacted. LM uses a simplified Hessian matrix in the following Newton-like update function:

$$x_{k+1} = x_k - [J^t J + \mu I]^{-1} J^t e \tag{28}$$

where J is the Jacobian. Further information can be found in the documentation released by Matlab [38].

Bayesian regularisation backpropagation was also considered for ability to handle more complex problems but the increased processing time did not produce a noticeably more accurate result. Scaled conjugate gradient backpropagation was also considered yet it is recommended for low memory situation and was not required for this system.

4 Pseudo Code Description

Historical stock data is loaded from Google Finance. This includes closing and opening price, and the time period for which the data is available. Following loading the data, Australian interest rates for that same time period are loaded and compound interest is calculated for the length of trading data available. A Neural Network is then trained with 70% of the stock price data, 15% validation and 15% testing. This is able to produce a time series of stock predictions that will be used in the stock simulation.

Once all data is generated it is fed into the simulation element of the code. It steps through each day valuating the opening price, utilising the trading strategy to either predict the next closing price or calculate a technical indicator. A trading signal of -1 (sell), 0 (hold), 1 (buy) is output and the transaction is undertaken on the opening price of the following day. This cycle continues for the period of historical trading data available. Throughout all transaction details are recorded.

When the simulation concludes all data is mathematically valuated to calculate the metrics outlined in Section 2.7 of this chapter. All data is then depicted in a stock movement graph or exported to an excel document.

For testing purposes the above process was put within another loop that went through selecting each of the 21 stocks for a given trading method, and this was within a loop choosing each of the trading methods.

So simply put a trading method was chosen, then run on each of the 21 stock simulation, then the data was output. Then another trading method was chosen and again run on the same 21 stocks. This process continued until each of the trading systems were evaluated.

5 Trading Strategies

A range of trading strategies were evaluated, addressing technical indicator performance, verse pure prediction based off the neural network as well as considering the two combined. As a base line a method of 'random' trades was used to evaluate the possibility of chance verse direct and purposeful profits. Below is a description of each of the trading methods used and their reference name going forward.

5.1 Random

As a means of evaluating the chance/luck in trade and comparing that to the decision methods used a set technique of trading on a 20 trading day cycle was implemented. A period of

20 days was chosen as that is four weeks of work days. Therefore, it involved simply trading every four weeks, without any consideration for the price or stock movement. Its reference name is 'Period Increment 20 Days'

5.2 Prediction

Two trading methods were used that were based off the Neural Network output solely. The first was 'Price Prediction'. This strategy would buy the maximum number of stocks if the close price for the following day was predicted to be higher than the opening price. Alternatively, the system would sell if the predicted next day’s closing price was lower than the current holdings. Therefore, ideally buying low and selling high. A similar method was used for the ‘Only Good Trades' method. This strategy followed ‘Price Prediction’ however if the sale price was lower than the price that the stock was purchased it would not sell. Therefore, only having good trades, that would ideally make profit. The final prediction method is 'Percentage Change', it was used to consider large changes and improve long term investment. It is based on ‘Price Prediction’ however it will only buy or sell if there is a change greater than 1% of what is owned.

5.3 Technical Indicator

A stock price technical indicator is a metric used by traders, often it is a simple rolling formula that addresses the movement to evaluate the future prediction. The algorithm is not dynamic and is based around strict rules. The three most common techniques were used. The first and simplest used was simply evaluating the gradient of the curve (Eq. 4), only buying stock when positive and selling when negative. The second method is 'Tech Indic Momentum' (Eq. 6), this method evaluated momentum a measure of the past price average and its tendency to change. If momentum is positive then purchases should occur, if negative then the stock should be sold. One of the most advanced technical indicators used is the Moving Average Convergence Divergence (Eq. 7-11), which addressed the moving average for 26, 12 and 9 day periods evaluating their expected movement. Again like momentum if a positive difference then buy else sell. This decision technique within the system is referred to as 'Tech Indic MACD'.

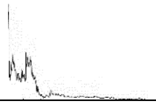
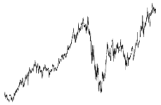
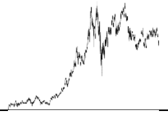
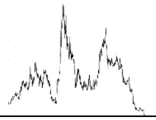
5.4 Combination

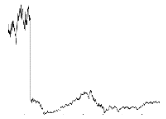
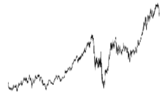
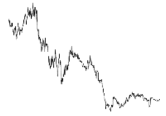
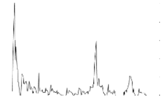
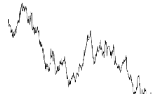
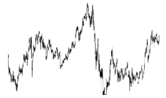
Momentum, gradient and MACD were combined each with price prediction. This meant that both decision methods had to hold true for a transaction to take place. The aim was to reduce the risk, erratic nature and short foresight of the Neural Network predictions. The combined techniques were called 'Price Pred and Momentum', 'Price Pred and Gradient' and 'Price Pred and MACD'.

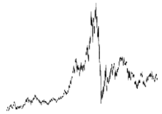
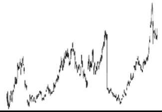
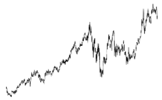
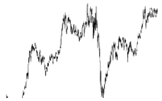
6 Stock to Evaluate

To evaluate the system a range of Australian stocks were chosen. Stock shape varied with at least one stock depicting a continued increase and decrease, sudden increase and decrease, only small movements, and stock above $80 and below $1 valuation. A range of industries were considered to gain a holistic understanding of the performance of the trading strategies. Table 1 presents the different companies and the unique aspects of their stock price.

Table 1. All Stock system has been tested on and their attributes

Stock	Company Name	Industry	Starting Price ($)	Ending Price ($)	Max Price ($)	Min Price ($)	Number of Trading Days	Characterisation of Simulation Period				Stock General Shape
								Increased	Decreased	Large Peak	Large Trough	
AKK	Austin Exploration Limited	Energy	2.25	0.016	10.7	0.013	2364		Yes			
ANZ	Australia and New Zealand Banking Group	Bank	11.38	27.85	37.05	9.78	4242	Yes		Yes	Yes	
APA	APA Group	Energy	2.29	8.7	9.7	2.25	3849	Yes				
BHP	BHP Billiton Ltd	Energy	6.25	17.91	49.95	6.25	4244	Yes		Yes	Yes	
BRK	Brookside Energy Ltd	Energy	5.4	0.008	29.6	0.008	2391		Yes	Yes	Yes	

BXB	Brambles Limited	Distribution	40.59	11.55	53.4	3.85	4244		Yes		Yes	
CBA	Commonwealth Bank of Australia	Bank	25.867	85.49	96.32	22.54	4243	Yes		Yes	Yes	
COH	Cochlear Limited	Medical	10.2	95.99	95.99	10.2	4244	Yes		Yes	Yes	
DSH	Dick Smith Holdings Limited	Retail	2.28	0.37	2.38	0.22	524		Yes			
GFF	Goodman Fielder Ltd	Distribution	2.06	0.675	2.67	0.39	2324		Yes			
GOL	ETFS Metal Securities Austrailia Ltd	Gold	55.6	139	178	51.26	3227	Yes		Yes		
MMJ	MMJ PhytoTech Limited	Medical	0.32	0.23	0.805	0.225	240		Yes	Yes		
MYR	Myer Holdings Ltd	Retail	3.88	1.21	3.99	0.85	1558		Yes			
NAB	National Australia Bank Ltd	Bank	28.2	30.2	44.44	16	4243	Yes		Yes	Yes	

QAN	Qantas Airways Limited	Transport	4.488	4.15	6.39	1.033	4234		Yes	Yes	Yes	
RIO	Rio Tinto Limited	Energy	21.82	44.65	156.02	21.315	4243	Yes		Yes	Yes	
RMD	ResMed Inc.	Medical	2.8	7.5	9.83	2	3982	Yes		Yes	Yes	
SIO	Simonds Group Ltd	Construction	1.75	0.93	1.75	0.845	285		Yes			
WBC	Westpac Banking Corp	Bank	11.25	33.43	40	9.166	4243	Yes				
WES	Westfarmers Ltd	Retail	16.641	42.09	46.43	11.88	4218	Yes			Yes	
WOW	Woolworths Ltd	Retail	5.2	24.95	38.83	4.7	4244	Yes				

7 Limitations

The current project was complex, undertaking a task addressed previously by thousands of corporations and individuals. Thus attempting to and succeeding at doing something with limited knowledge and technical skills is a huge limitation. The complexity of the market, trades and function is also a huge limitation as modelling that complexity accurately will be near impossible, however it is hoped that with assumptions this will be resolvable.

An unforeseen limitation involved the restrictions on commission free trading platforms. Currently within Australia access to such a service is not available and thus testing this trading system on real life stock movements was not possible. Rather the focus of the research was devoted to assessing technical indicators versus pure neural network predictions. Once this technical limitation has been addressed further research can continue into the practice of using the trading system.

8 Errors

Stock prices were obtained from Google Finance, it is possible due to the huge volume of transactions and data that the values may not be completely accurate particularly for historical data coming from more than ten years ago. Slippage, the difference between choosing to purchase and actually being able to purchase a share could not be represented in the simulation accurately and thus cannot be valued, therefore creating error. The main source of error that could have occurred was miss-matched indexing in the simulation, i.e. predicting for the 5th of November, but purchase prices being the 3rd of November. This error was avoided by appropriate quality assurance testing and data interpretation. These techniques included third party review, data verification and validation.

9 Summary

The system design has been clearly outlined in this chapter. The structure of the system and the iterative loops depict the consistency of the design. Each element has been detailed from the strategies used to each stock analysed. Finally, the importance and consideration for errors and limitations were have been discussed emphasising that all concerns were managed and did not impact on the integrity of the results. The details and structure provided within this chapter not only builds confidence in the results found in this body of research but also allows for future development and testing of the designed system.

Chapter 4: Results

The system was run on 20 stocks and 10 decision methods, this meant 200 simulations were run in total, this data has been summarised in the following section, split into an overall analysis and depiction of results in specific industries and stock shapes. The data outlines that a pure Neural Network prediction method is ultimately the best option for stock market trading. It outperformed every method in six of the eight industries and every single shape categorisation. These findings indicate that it would be an effective means of implementing a practical trading platform, once the commission consideration is overcome.

To thoroughly test the stock market trading strategies, the system was run on 21 stocks, simulating day to day trades for the length of the data that was available for that specific stock. These values were recorded and tracked allowing for stock evaluation and performance metrics to be established. The following is an overarching understanding of the results. A summary table has been presented normalising annual profit against each of the variables.

Section 1, discusses at a high level an evaluation of the trading strategies analysed. The section begins by first establishing the evaluation structure, it continues by looking at a summary table of industry and shape performance. Following each element is drilled down upon, evaluating each industries performance by trading method. A similar evaluation is then done for shape, looking at the performance for trends, and trough/peaks. An overall graph depicts the performance of each strategy by the analysed stocks. The chapter concludes with a summary of the findings after undertaking this body of research.

1 Trading Strategy Evaluation

1.1 Overall

To gain an understanding of the performance of each method the following two tables were established looking at the decisions method on stocks categories by industry (Figure 12) and shape (Figure 13). The data has been normalised with the best performing decision method in each section receiving 100% and all others as a fraction of that. All negative values indicate that performance method lost value over the trading period. Colour mapping has been used to simplify the understanding. It is evident that prediction outperforms all methods and when combined with technical indicators improves their performance, to the determent of its own.

1.1.1 Industry

Performance										
Trading Strategy		Industry								Industry Overall Performance
Categorisation	Decision Method	Bank	Construction	Distribution	Energy	Gold	Medical	Retail	Transport	
Random	Every 20 Days Buy/Sell	11%	-96%	100%	21%	52%	-16%	-17%	-642%	-73%
Prediction	NN Price Prediction	100%	100%	96%	100%	23%	100%	100%	-36%	73%
	Only Positive Trades	47%	-91%	-29%	20%	100%	44%	-2%	100%	24%
Technical Indicator	Percentage Change	2%	-105%	-44%	13%	92%	-5%	-7%	-470%	-66%
	Momentum	3%	-25%	-38%	-3%	55%	-39%	1%	40%	-1%
	MACD	6%	-55%	-35%	-4%	64%	38%	-21%	-77%	-10%
	Gradient	6%	2%	-34%	-1%	67%	-11%	-6%	-290%	-33%
Prediction and Technical Indicator	Prediction and Momentum	9%	14%	-12%	-1%	25%	-8%	8%	82%	14%
	Prediction and MACD	19%	-8%	13%	-1%	19%	83%	47%	-384%	-26%
	Prediction and Gradient	62%	36%	-21%	18%	82%	-2%	57%	-67%	21%

Best Performer

Worst Performer

Figure 12. Evaluation of Trading Strategies by Industry

1.1.2 Shape

Performance								
Trading Strategy		Stock Shape Categorisation						Stock Shape Overall Performance
Categorisation	Decision Method	Increased	Decreased	Large Peak	Large Trough	Large Peak & Large	No Sudden Movements	
Random	Every 20 Days Buy/Sell	22%	-37%	-16%	75%	53%	-12%	14%
Prediction	NN Price Prediction	100%	100%	100%	100%	100%	100%	100%
	Only Positive Trades	48%	-41%	20%	30%	64%	9%	22%
Technical Indicator	Percentage Change	21%	-60%	-28%	-9%	56%	-12%	-5%
	Momentum	8%	-46%	-54%	-10%	18%	-3%	-15%
	MACD	10%	-23%	22%	-10%	24%	-11%	2%
	Gradient	9%	-27%	-25%	-12%	26%	-2%	-5%
Prediction and Technical Indicator	Prediction and Momentum	9%	-14%	-11%	4%	8%	4%	0%
	Prediction and MACD	13%	55%	85%	7%	2%	19%	30%
	Prediction and Gradient	50%	-7%	-25%	24%	89%	34%	27%

Best Performer

Worst Performer

Figure 13. Evaluation of Trading Strategies by Stock Shape Categorisation

1.2 Industry

It is clear from Figure 14 that energy and banks are the best industry for investment, with construction being the least profitable. Furthermore, for every industry prediction is within positive annual profit, albeit sometimes small. This cannot be said about any of the other decision method categorisations.

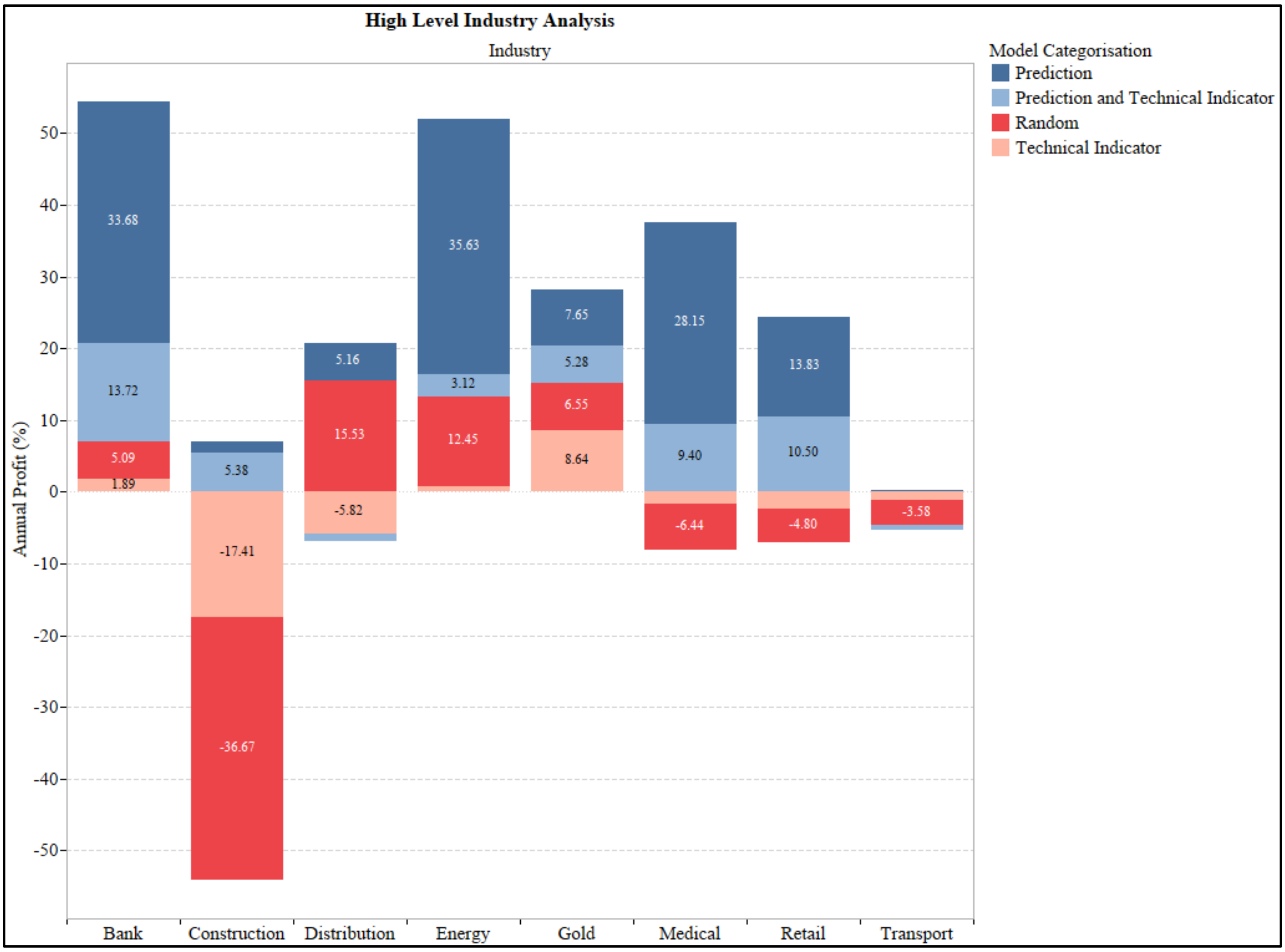


Figure 14. High level performance of each model categorisation by industry

1.3 Shape

1.3.1 Trend

Figure 15 is similar to the previous bar graph, however it is split into those shares that increased in value over the simulation and those that decreased. This outlines the power of prediction as the average annual profit is positive for both increasing and decreasing stock, with indicators performing the worst in decreasing stock.

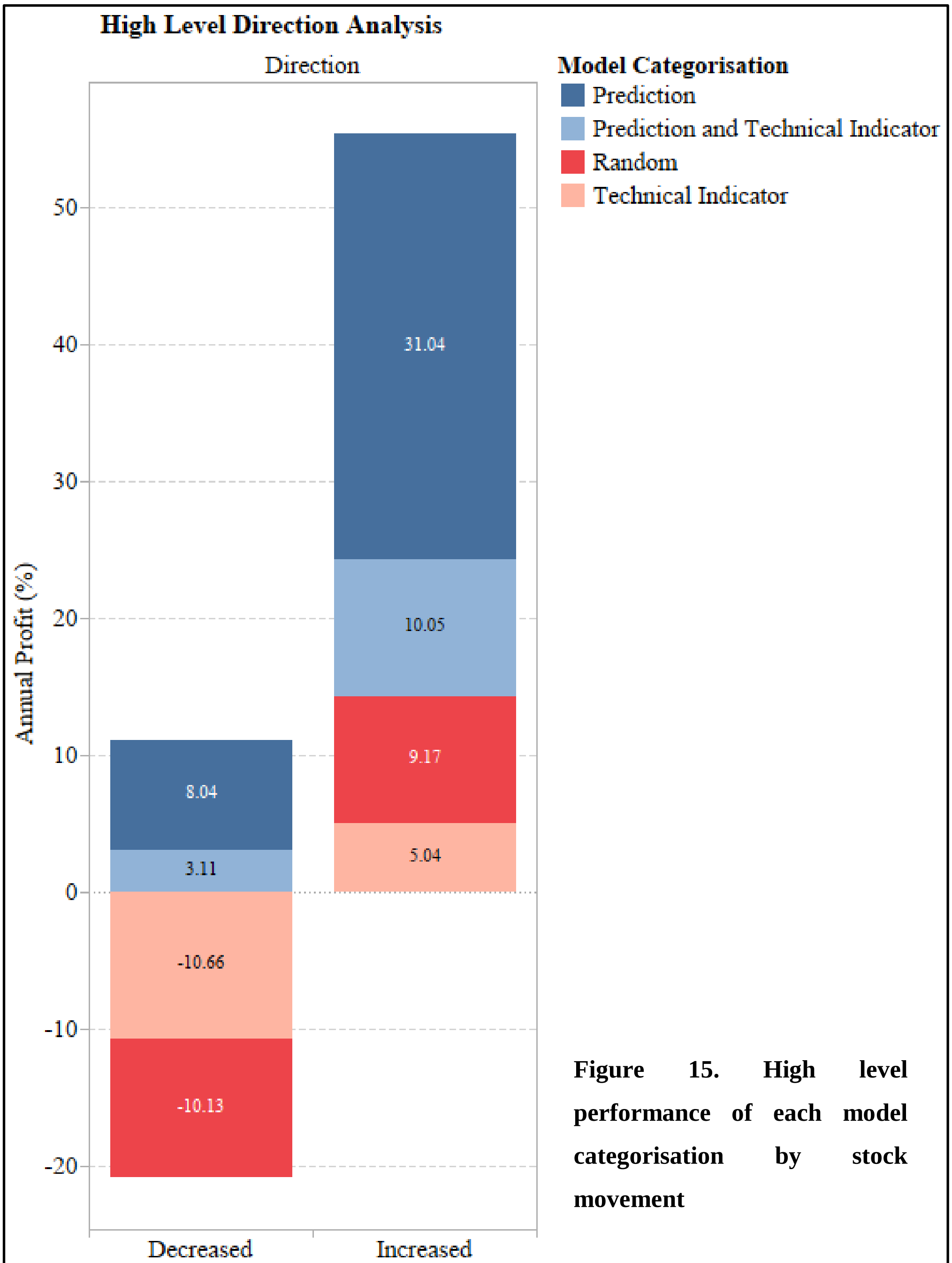


Figure 15. High level performance of each model categorisation by stock movement

1.3.2 Trough/Peak

Again Figure 16 outlines how prediction out performs all other methods, with its average annual profit always positive. It is also interesting to note that for large peaks it performed the best and was able to take advantage of the swing in increase. Furthermore, the monthly purchase cycle categorised as random performed best in the large trough period, this is likely due to the inconsistency of trades and was not swept up in the decline.

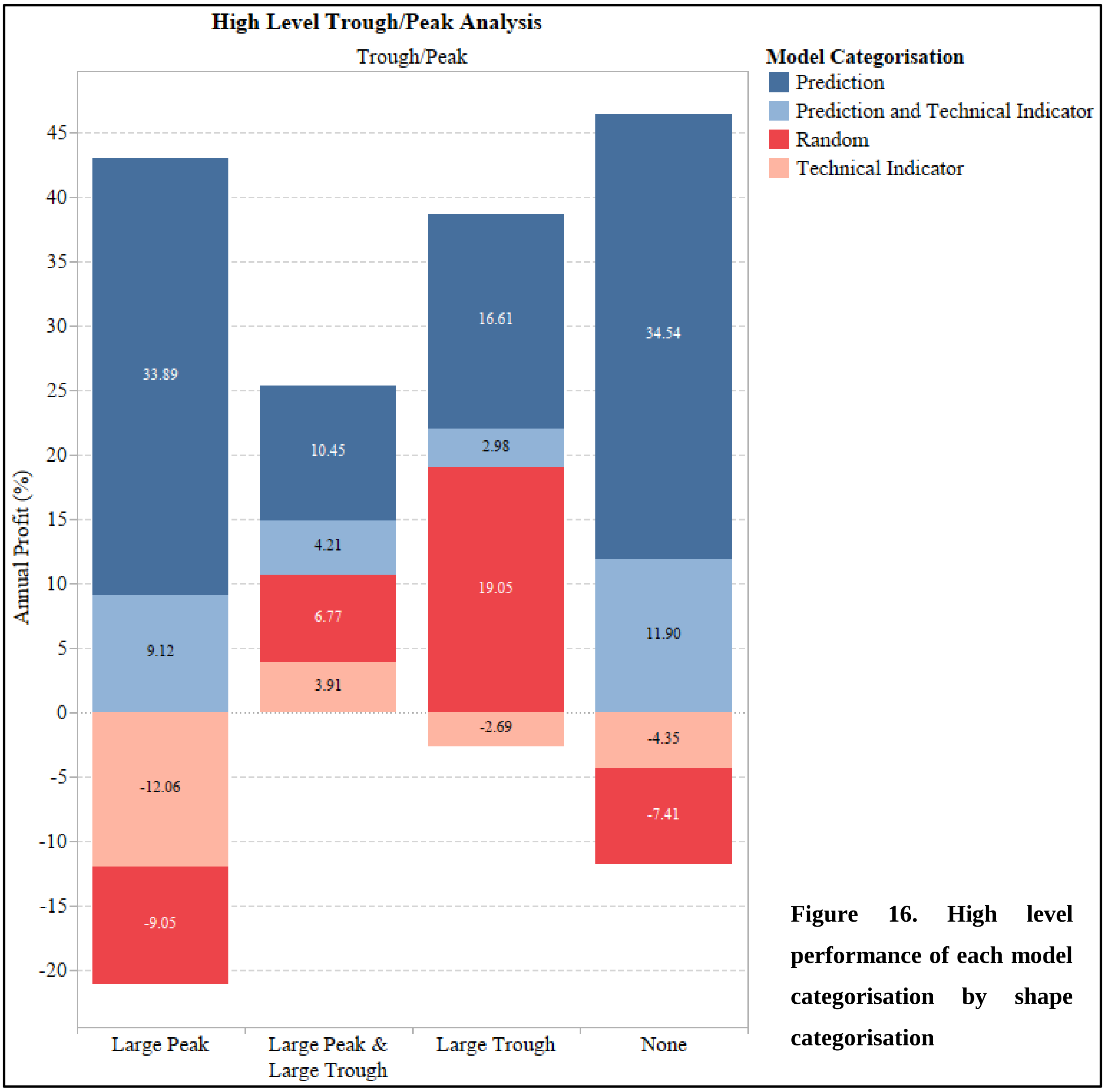


Figure 16. High level performance of each model categorisation by shape categorisation

1.4 All Industries by Strategy for Average Annual Profit

Figure 17 depicts the average Annual profit across the 21 stocks that were analysed for each trade strategy. The performance of prediction methods above that of pure technical indicators is clear. With pure Neural Networks achieving an average annual profit of 36%, 24% higher than its next closest competitor. It is important to not only consider these figures individually, as they are an aggregation of the results and could manipulate the outliers. It is import thus for further analysis, outlined in the next chapter. It is also important to note that this profit is substantially lower then initial research indicated. This is as a result of adding in ten more stocks, each of which was chosen for its decreasing shape.

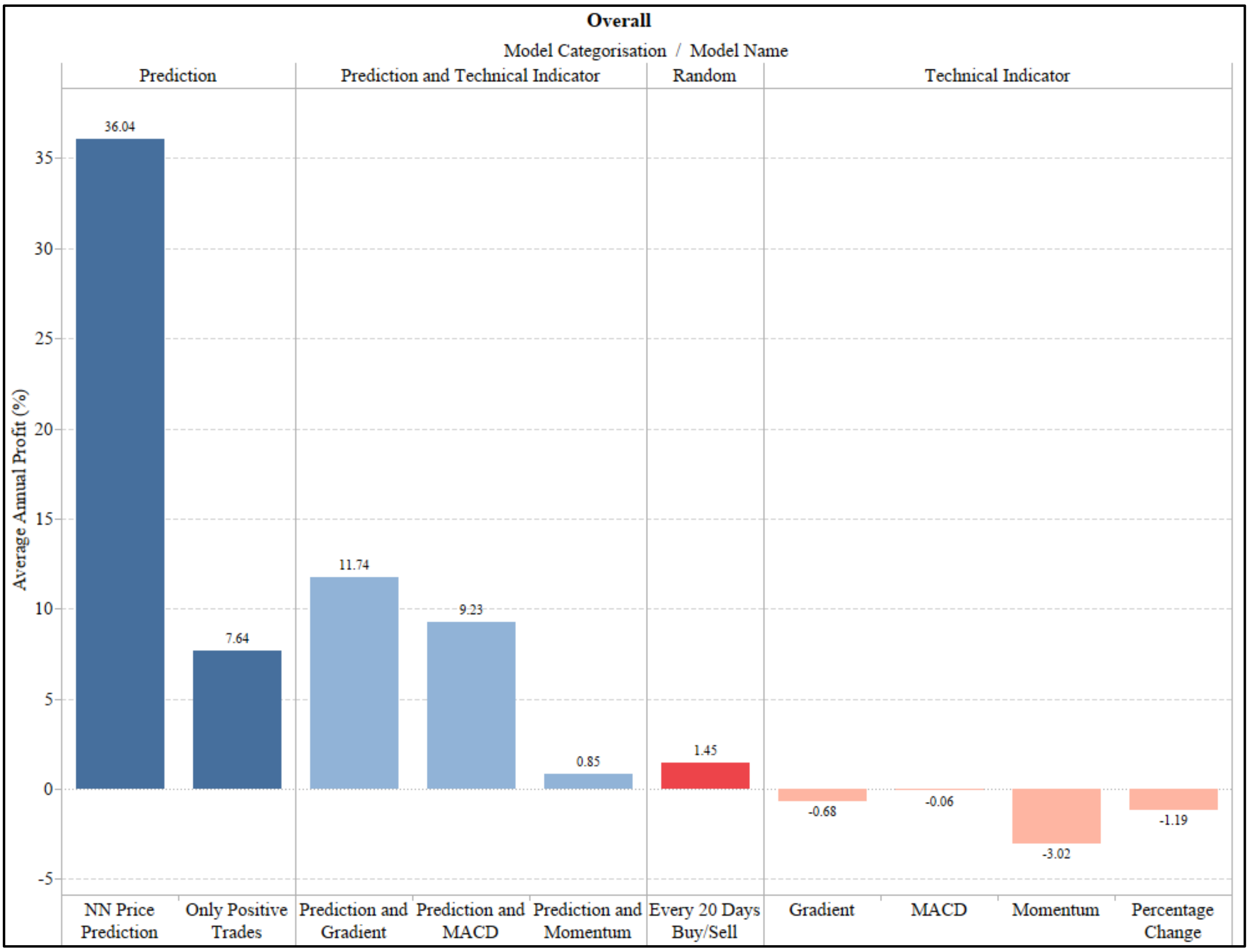


Figure 17. Each trading strategies' average performance across all tested stock

1.5 Stock Performance by Strategy Evaluation of Profit

Figure 18 outlines the pure prediction of NN's outstanding performance depicting the profit of each stock relative to the other trading methods. The method had very few stocks with losses. Depicting its strong potential within a real trading environment.

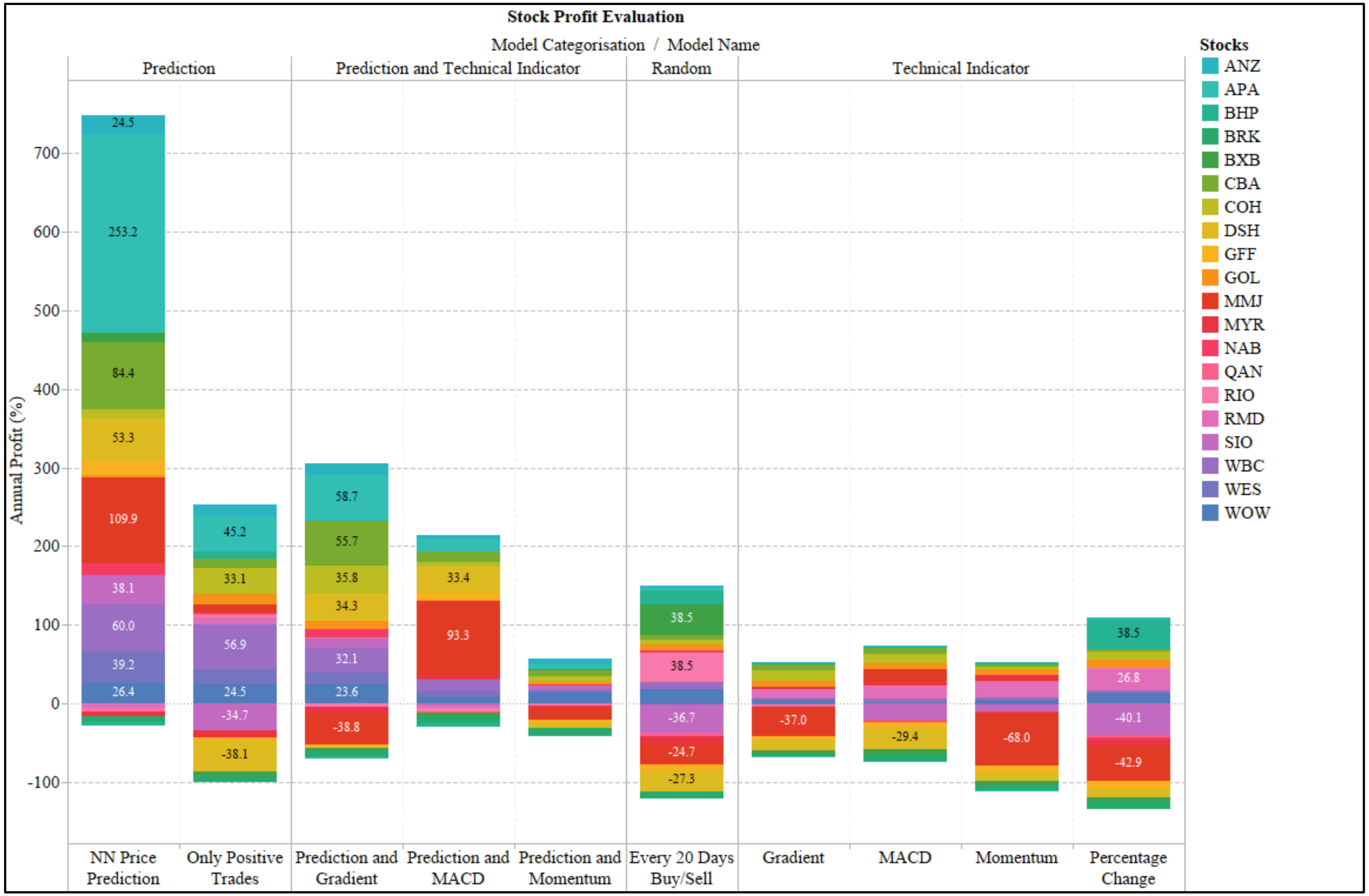


Figure 18. Each trading strategy depicting the annual profit per stock.

2 Summary

The aforementioned figures depict a range of lenses to access the performance of the trading strategies. The story starts with a broad view outlined in Figure 12 and Figure 13. Both convey pure predictions outstanding performance, within all industries and shapes, except gold and transport, it was the highest performer. The performance in declining stock is of great importance as it was the only trading method to make a profit. The performance across the shape and industry categorisation is reiterated in figures Figure 14, Figure 15 and Figure 16. The final two figures of the chapter have a more granular evaluation perspective. However, they convey the same story. Pure prediction greatly outperforms the other decision methods. Figure 17 shows pure Neural Networks achieving an average annual profit of 36%, 24% higher than its next closest competitor. Figure 18 depicts the small number of losses and respective values compared to non-neural network decision methods. Therefore, the range of figure conveys a clear story of pure Neural Networks predictive and trading capabilities.

Chapter 5: Evaluation

The ultimate aim of this body of research was to identify the ‘best’ trading strategy available that would be applicable and viable in a real trading environment. Chapter 4 results give a broad summary, indicating that pure stock prediction using neural networks is not only the simplest but also the most profitable. However, this does not provide the full story. To do so, an in-depth analysis, accessing clear evaluation criteria of risk, profit and complexity must be undertaken to determine the successes and pitfalls of each method. This chapter aims to establish clear criteria of success and evaluate each method according to their industry and stock shape, as well as discussing how this will impact on the practical capability of implementing the strategy in a realistic market.

This chapter is broken down into the following structure. Section 1 establishes clear evaluation criteria, of profit, complexity and risk. Sections 2, 3, 4 then look into each of these criteria individually. Section 5 addresses the applicability of the established trading method within a realistic market, considering future concerns and possibilities. The chapter concludes with a summary of the in-depth analysis outlining key findings.

1 Evaluation Criteria

To ensure a clear indication of the capabilities of each method they will be assessed upon three criteria;

1. Profit – the simplest criteria used will evaluate the annual profit (Eq. 20). So the Final sum available less the initial investment. In many cases negative profit was achieved an undesirable approach. As a result, strategies will be compared by their relative success with only positive overall profit being seen as a desired outcome.

2. Complexity – as an evaluation criterion is harder to address and define. For the purpose of this analysis complexity will be considered by the skill required to implement the trading technique and the frequency of trading. Therefore, a difficult system to implement that trades daily would be considered extremely complex. Whereas one that is a simple formula that is easily applicable, but results in trades once a month, will be of low complexity.

3. Risk – Due to the large number of variables and influences risk is the most difficult criteria to assess fairly. Therefore, within this analysis it will be determined by a combination of, an average of how much is lost or gained per trade, and an evaluation of the likelihood of a loss verse profit for a trade. Furthermore, number of instances of loss verse profit will also be evaluated as well as the number of times profit was above that of a long term bank investment.

2 Profit

2.1 Trading Strategy by Industry

From Figure 20 a great deal of information is evident. The first is the overarching success of the Prediction Strategy. It outperforms the other methods in 75% of the industries and has the smallest number of losses. It is also important to note that loss was only made in one industry, transport, for which each method was not able to make a profit. Prediction still performed the best. Conversely Technical Indicators performance is the least impressive, even below the random trading method, having a loss within 5 of the 8 industries. As a result of these two behaviours the combination of the two methods met in the middle group only having a loss in two industries. However, the profit that would have come from simply using a prediction method was lost. The overarching performance is clear, that prediction surpasses every other method, with great profits as well as few losses.

Figure 20 does not only outline the performance of the trading strategies it also gives insight into industry performance and stock investment choice. In only banking, energy and gold were all methods able to make a profit, which ultimately is not a surprise as those industries are usually associated with sustained growth and performance. Of the three industries energy had the highest average profit of the four strategies with a profit of 18.73%, drastically higher than that of any bank investment. Thus, it is reasonable to extrapolate that real implementation of a trading system should be focused on these industries as means of reducing risk and ensuring long term profits and performance.

A note is that gold was completely reversed with the expected performance based on the other industries. Technical Indicators had the highest return with prediction having the lowest. From inspecting Appendix A and evaluating the Price Predictions performance it is evident that initial management was highly successful until a sudden increase threw the method off. It seemed unable to readjust and resulted in a slow decline of profit. Reaction to movement will be evaluated more closely in the next section.

Although Prediction was not the highest performing strategy across each industry its clear success above the other methods was clear, especially within the energy and banking industry.

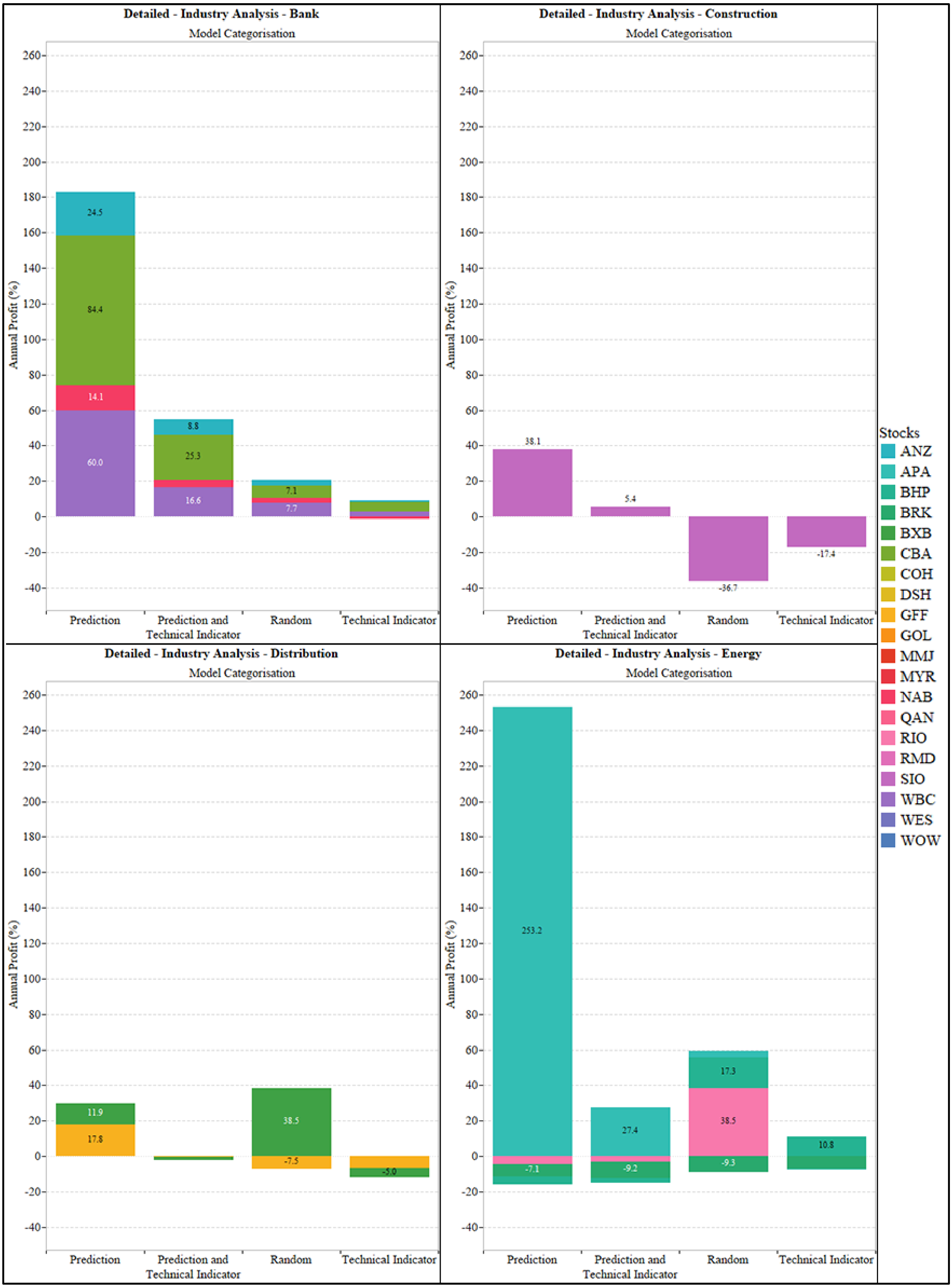


Figure 19a. Profit for each share in an associated colour, broken down for each industry and decision category

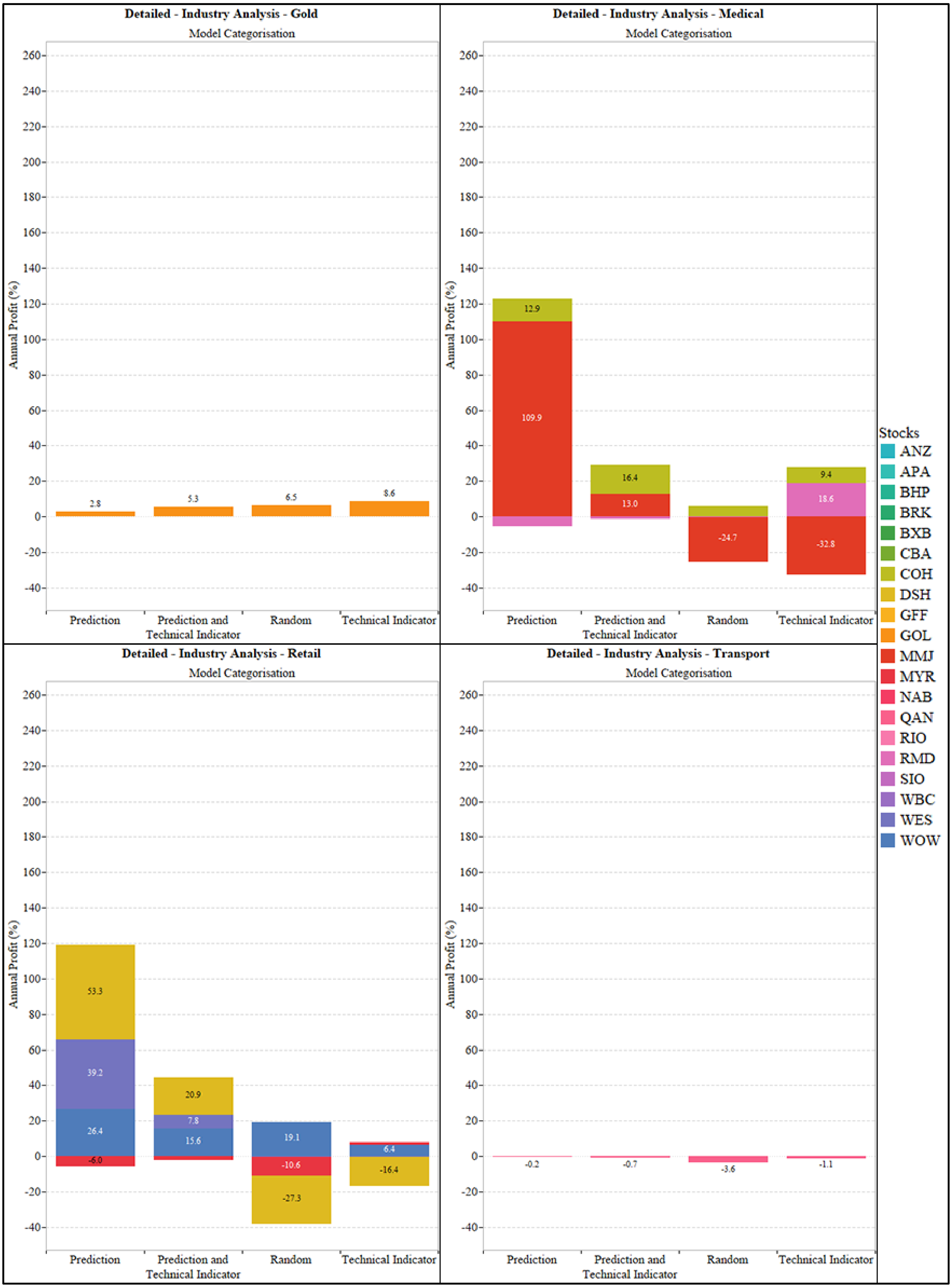


Figure 20b. Profit for each share in an associated colour, broken down for each industry and decision category

2.2 Trading Strategy by Stock Shape Categorisation

2.2.1 Increasing Stock

When looking at Figure 21 it is clear that all methods perform fairly well on increasing stock, with Random and Technical Indictor only having 1 stock that was not profitable. However, Prediction methods way out performed the other methods in total profit received. Technical Indicators had an annual average profit across increased stocks of 4.33% whereas prediction has 43.15%. Therefore, it appears for increasing stocks Prediction methods have higher returns, yet technical indicators have lower risk. This is evident in Figure 21**:** Increased Large Peak, where Prediction and technical Indictors has reduced losses compared to prediction but increased profits compared to technical indicators.

Reaction to sudden change and the ability for each method to do so is also clearly outlined. It is evident that the Prediction strategy when not impeded by sudden change is able to understand and develop a strong pattern for the stock allowing for clear prediction and in turn large profits. Whereas the other methods are faster to react, as evident in their improved performance for peaks and troughs. Therefore it is clear that Prediction methods establish strong relations that do not adjust quickly whereas technical indicators cannot develop strong, long term patterns but are able to change on the fly. Thus, the combination of the two reduces risk, but also reduces potential profit.

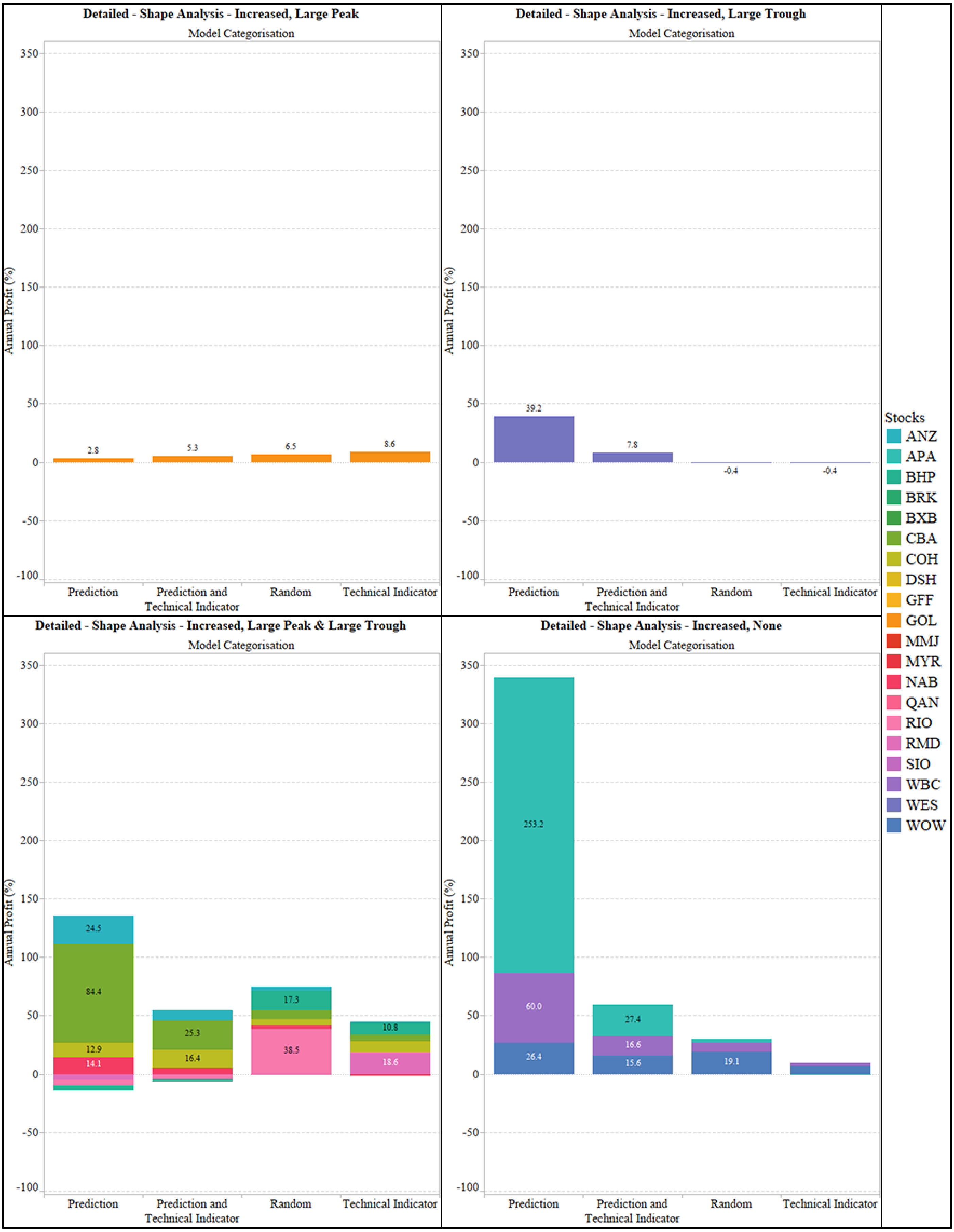


Figure 21. Profit for each share in an associated colour, broken down for "decreased" stock, their erratic movement and decision category

2.2.2 Decreasing Stock

Decreasing stock shape is of great interest when evaluating a trading system as it is relatively easy to make profit and reduce risk if the stock is on a constant positive slope. However, it is not possible to select a stock that will always on the incline. Therefore, having a trading method that can make profit even in a decline is a huge benefit and greatly reduces overall risk and concern for the trading system.

From Figure 22 Predictions comparative performance is clear, only having a loss on two stocks, greatly outperforming all other methods, taking particular note of technical indicators which made no profit. Unlike the previously discussed impact of combining Prediction and Technical Indicators, for decreasing stock the technical indicator aspect greatly limits the predictions method from benefiting from minor fluctuations in the movement of the stock. As a result, the combination of the two both increases risk of loss and decreases profit. One must therefore be aware of this concern when implementing the trading system into reality as it is not possible to always select increasing stocks. Again the ability for prediction to adjust to sudden movements is clear as when the stock is more consistent profits sky rocket.

As a final note when looking at decreasing stock it is important to understand the huge profits for prediction in Figure 22**:** Decreased, Large Peaks. The stock in this graph is MMJ, which began high, fell quickly to below $1 and had a sudden increase before small fluctuations again, below $1. This shape can be very profitable for the prediction method as the low value means great percent increases per unit increment, i.e. the change from 0.04 to 0.05, is much larger a profit than 20.04 to 20.05. The Prediction trading method flourishes on these small changes. Large profits however come at a great cost as at such a low price it is easy to make large loses as well or potentially even have the price reach 0. Thus, when choosing stocks in which to invest this element must be considered.

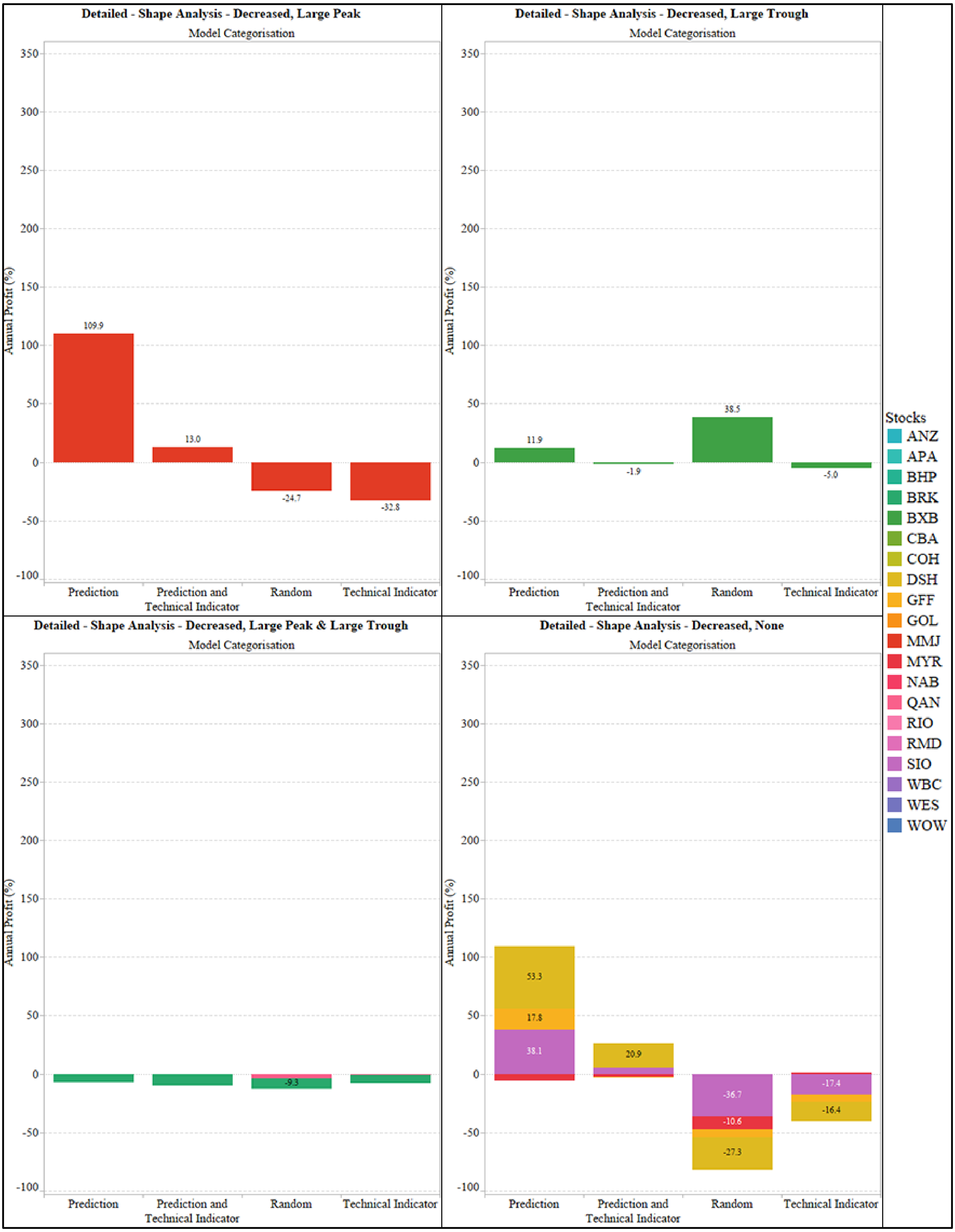


Figure 22. Profit for each share in an associated colour, broken down for "increased" stock, their erratic movement and decision category

2.2.3 Summary

The above analyses outlines two important differences between technical indicators and prediction methods. The first is their reactivity. Prediction methods can establish a long term pattern yet when there is sudden change their time to adapt is slow and can be costly, particularly within the stock market. Technical indicators on the other hand are able to react quickly, yet as a result are unable to develop longer term understanding and direction, therefore reducing sudden risk but limiting long term gains. Taking into account increasing and decreasing shape, technical indicators cannot perform well on decreasing stock as it limits trading to a hold. However, prediction trading is able to take advantage of minor movements and in turn can benefit from fluctuations.

3 Complexity

As discussed previously complexity is defined as a combination of difficulty of implementation and frequency of trades. With regards to implementation, Technical indicators is the most simplistic; they are easily calculated formulas that require at most a month of historical data. Prediction methods using Neural Networks are the second most complicated, obviously due to their technical nature and complex calculations but also due to the requirement for large quantities of historical data. The combination of the two is the most complex as it requires the resources, understanding and processing power of both methods as well as evaluating the weighting of how the two methods should be combined. Therefore, it is important to evaluate whether this complexity and increased processing requirements is beneficial.

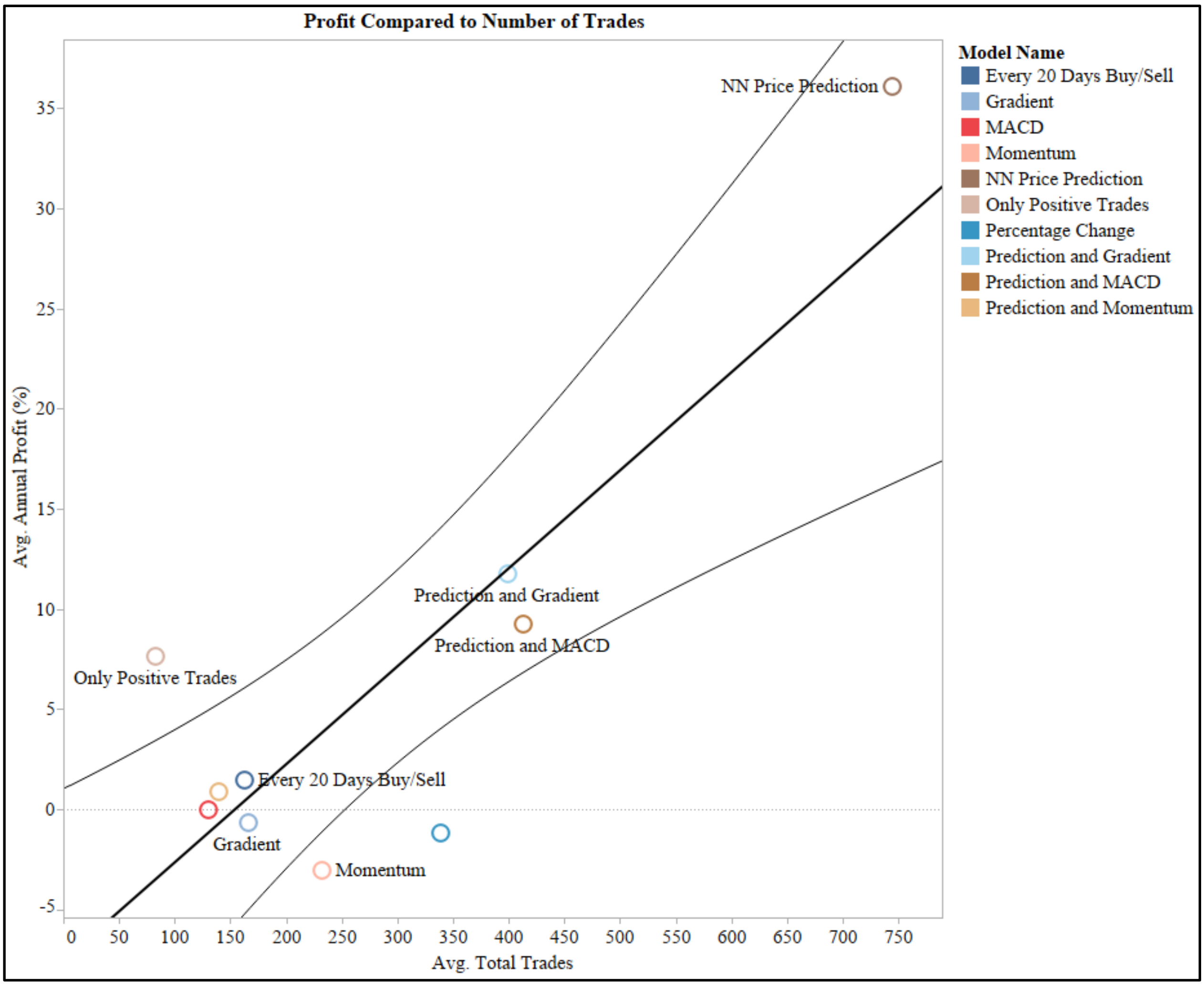


Figure 23. Comparison of average number of trades, for the associated average profit for each trading method

To evaluate the impact of complexity and required processing power on profit Figure 23 will be used as it outlines the relation between average annual profit and the average number of trades required to achieve that profit. The graph outlines a clear linear relationship between number of trades and associated profit. This is clear as pure prediction compared to Prediction and Gradient outlines that an increase of 46% in the number of trades resulted in a 67% increase in profit. This relationship has been discussed in the shape evaluation, as increased number of trades allows for the system to benefit from small fluctuations. This concept has been evident for some period of time in trading systems of large organisations that function within fractions of a second.

This data outlines that although the combination strategy is the most complex and processing power heavy it does not result in the largest number of trades, as the Technical indicators limit and restrict, reacting quickly to changes. The most complex by number of trades indicates increased profits. Therefore, the most complex system is not required for trading, but there does require some level to succeed.

4 Risk

Risk evaluation is complex as a specific number for each trading method cannot be evaluated. However, a range of indicators can suggest the likelihood of a system losing. Unlike the above evaluation Methods Risk does not address profit, i.e. how much would be lost verse how much would be gained relative to one another. The following two methods address what the likelihood is for each strategy to make a greater profit than investing in a bank account over the same time period. The second looks at the likelihood of having a stock investment losing money over time.

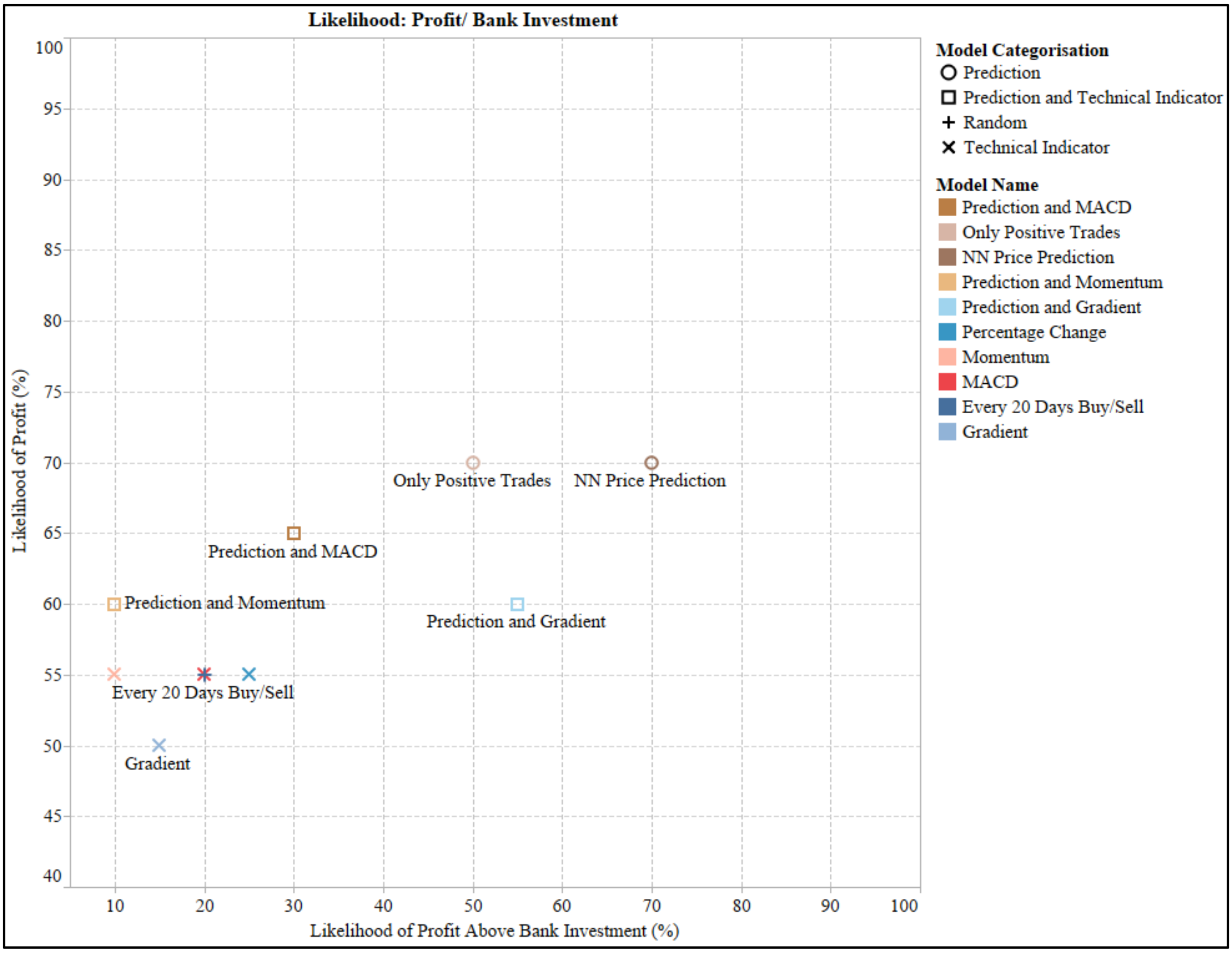


Figure 24. Likelihood analysis comparing chance of making a profit and chance of outperforming a bank investment of equal value and time series

To calculate the two likelihoods for each strategy Eq. 29 and Eq. 30 were used:

Likelihood of Profit

$$\left(\frac{\#\ of\ stocks\ with\ profit}{\#\ of\ Stocks}\right) \times 100 \tag{29}$$

Likelihood of Profit Above Bank Investment

$$\left(\frac{\#\ of\ stocks\ with\ profit > bank\ investment}{\#\ of\ Stocks}\right) \times 100 \tag{30}$$

4.1.1 Risk on Profitable Investment

Figure 24 depicts the likelihood of making profit using each strategy. Values were simply calculated by dividing the number of profitable stock investments by the total number of stocks, 20. Due to technical indicators inability to make profit on decreasing stocks, their likelihood is substantially lower than that of pure prediction. The research indicates that one is more likely to make profit trading once a month, rather than using technical indicators. Prediction techniques both performed well achieving 70% likelihood. Again it is important to stress that these values do not indicate overall profit as size is not considered, rather a boolean representation.

4.1.2 Investment Compared to Bank Interest

Although profit is important it is irrelevant if the profit is not higher than that of an equivalent initial investment in a bank account over that period of time. As discussed in the methodology, historical data on bank investments were imported into the system to give a control and ‘yard stick’ to access the success of the investment technique. Figure 24 depicts that only two methods would make more than a bank investment 50% of the time. Pure NN price prediction achieved a chance of 70%. As this value was often drastically larger than bank investment, with loss only slightly below bank investment, it is evident that using such a trading strategy would be a reasonable alternative to investing in a bank account.

5 Real World Extrapolation/Applicability

This body of research has furthered that of the literature. It has moved from focusing on the pure theoretical application of NNs; only focusing on one stock and how accurate the prediction could be [15], or evaluating straight profit on a few stocks. Rather, the main focus has been on real ASX stock data, evaluating a range of methods and addressing their success through a variety or metrics. Most importantly is the success has been measured on practical and factual data such as the comparison against bank investment.

The research has been restrained by not being able to implement the trading system in a real environment due to the technical limitation, however it has acted as a bridge, connecting the theoretical study of prior research and the business and consumer work of profit, price and growth.

Once there is a means for commission free trading, a trading platform that utilises Neural Network Decision making will not only be viable, it will be profitable. The simple design build for thesis as a proof of concept has proven that profit is possible for and can be tailored to the appropriate industry to insure maximum profit at a reduced risk.

6 Summary

To accurately evaluate each trading strategy three clear evaluation criteria were established; profit, complexity and risk. An assessment of profit conveyed the higher returns from utilising a neural network decision method. Across all industries except gold, it was the highest performer, rarely having negative returns. By shape neural network decision methods again out performed all other strategies. It is important to note that it was the only method that continued to make profits for a decreasing stock, a feat which has historically been difficult to achieve. When addressing complexity there was no clear indication that high levels of complexity were required nor beneficial. However, simplicity did not increase performance either, a middle ground was outlined as the best option. Risk was difficult to consider, yet two metrics were developed to evaluate the chance of making a profit, and surpassing a bank investment. From this data a pure Neural Network trading strategy surpassed all other methods, achieving a 70% chance of making a profit, each time surpassing that of a bank investment. Such a high likelihood is promising. Each of the analysis paradigms not only depicted the strength of Neural Network prediction but also outlined how improved results can be achieved. Profit conveyed the correct industries to focus on, complexity addressed the structure that was best to implement and risk gave a numerical value of consideration indicating each methods potential within a real trading environment.

Chapter 6: Conclusion and Future Work

1 Conclusion

The importance of Artificial Intelligence and its impact on society has been evaluated and discussed. Thus looking into its potential application within business is essential. The literature reviews outlined areas of consideration and improvements over time with ANN, however there was also a clear gap in practical application and potential evaluation. The proposed system has a huge place and great potential within the research area. From early development it is evident that huge leaps have been made with the trading system, already producing annual profits of upwards of 100%. The system currently has concerns with consistently declining stocks, however, with diversification this risk can be reduced. At sudden times of downturn, the system is still able to grow profits. Initial findings indicate prospective and potential of the system in prediction. With improved decision making techniques, consideration of technical indicators and hard stop implementation, the results of the system are only going to improve. Thus, this documentation outlines the potential to implement and utilise the system within a real trading environment.

The findings of this thesis have been promising, outlining the potential for profitable personal, consumer trading systems and stock advice. The designed and tested method was not only successful for increasing stocks, it also performed well for those which were decreasing. The system was slow to react to sudden change yet the benefit of frequent trades that take advantage of market fluctuations allows for large profits, outweighing the small losses that can occur. Furthermore, the research has identified industries of focus as well as those that should be avoided. Therefore, the profit element of the design has a strong foot hold. The complexity of the system as outlined does not play a large role in the performance, however the importance of frequent trades has been outlined and its linear relationship to profit. Finally, the risk of the system was discussed, emphasising that a trading system does not eliminate risk, however it does reduce it, achieving profit 70% of the time.

It is evident that once the limitation of stock trading and commission have been removed, which is already in action with the United States, the proposed trading system will be poised to take advantage of the market, benefiting society as a whole and the individual.

2 Future Work

Due to the limitations on technology, time, knowledge and experience all desired work could not possibly be accomplished. However, there are a variety of options for how this potential research could be furthered. One could focus on either the simulation parameters, looking at improving the functional system or bringing it to a closer representation of reality. The second focus could be on implementing the trading approach into a real stock trading market.

2.1 Stock Market Simulation

The stock market simulation used within this body of research was limited in a variety of ways. It did not include commission values and was not able to address the impact of slippage within the environment. Commission can easily be included, however a profitable system that included commission would be a much harder task. Thus, further focus could be put towards this area. With regards the slippage consideration, to accurately represent the delay between what price a stock can be purchased and what price another individual is willing to sell is difficult to construct without implementing some hard number or gap. Research could be done into calculating this impact and evaluating how it would impact a Neural Network trading platform. Finally, the largest area of improvement could be focused on using Artificial Intelligence to not only pick the price but also the stock and percentage of capital that should be invested. This task would not be simple as the range of choice, constant change and number of options would require a large amount of processing power to handle, let alone test and evaluate. Thus it could potentially be a task handled further in the future once there has been technological improvements.

2.2 Practical Implementation

If possible a more desirable future piece of work would be the implementation of a Neural Network trading system into the practical world. Actively choosing when to buy and sell stock, rather than focusing on a simulated environment. Such a task would require complex API integration into trading platforms as well as constant and accurate data sources. Furthermore, depending on the frequency of trades it may require larger sums of initial capital to be invested. Such an implementation would not be easy and would require a range of skills, and risk evaluation. This is all assuming the issue with commission is solved, be it by a decision method that is profitable with commission or a commission free environment.

Bibliography

[1] N. Manikandan and S. Subha, “Software design Challenges in Time Series Prediction Systems Using Parallel Implementation of Artificial Neural Networks,” *The Scientific World Journal,* pp. 1-10, 2016.

[2] C. Tilakaratne, S. Morris, M. Mammadov and C. Hurst, “Predicting Stock Market Index Trading Signals Using Neural Networks,” *Advances in Artificial Intelligence,* vol. 5360, pp. 522-531, 2008.

[3] T. Aamodt, “Predicting Stock Markets with Neural Networks,” University of Oslo, Oslo, 2015.

[4] R. Dash and P. Dash, “Efficient Stock Price Prediction Using a Self Evolving Recurrent Neuro-Fuzzy Inference System Optimized Through a Modified Differential Harmony Search Technique,” *Expert Systems With Applications,* vol. 52, pp. 75-90, 2016.

[5] W.-C. Chiang, D. Enke, T. Wu and R. Wang, “An Adaptive Stock Index Trading Decision Support System,” *Expert Systems With Applications,* vol. 16, pp. 1-36, 2016.

[6] F. Allen and R. Karjalainen, “Using Genetic Algorithms to Find Technical Trading Rules,” *Journal of financial Economics,* vol. 51, no. 1, pp. 245-271, 199.

[7] B. Vanstone and G. Finnie, “An Empirical Methodology for Developing Stockmarket Trading Systems Using Artificial Neural Networks,” *Information Technology Papers,* pp. 1-18, 2009.

[8] T. Hellstrom and K. Holmstrom, “Predicting the Stock Market,” *Technial Report Series IMa-TOM-1997-07,* vol. 7, no. 1, pp. 1-37, 9 August 198.

[9] R. Dase and D. Pawar, “Application of Artificial Neural Network for Stock Market Predictions: A Review of Literature,” *International Journal of Machine Intelligence,* vol. 2, no. 2, pp. 14-17, 2010.

[10] J. Bridle, “Alpha-Nets: A Recurrent 'Neural' Network Architecture with A Hidden Markov Model Interpretation,” *Speech Communication,* vol. 9, pp. 83-92, 1990.

[11] L. K. Hansen and P. Salamon, “Neural Network Ensembles,” *IEEE Transactions on Pattern Analysis and Machine Inteligence,* vol. 12, no. 10, pp. 993-1002, October 1990.

[12] S. Grossberg, “Nonlinear Neural Networks: Principles, Mechanisms, and Architectures,” *Neural Networks,* vol. 1, pp. 17-61, 1988.

[13] A. Shamseldin, “Application of a Neural Network Technique to Rainfall-Runoff Modelling,” *Journal Of Hydrology,* vol. 199, pp. 272-294, 1997.

[14] M. Reese, “Application of a Time-Delay Neural Network to Promoter Annotation in the Drosophila Melanogaster Genome,” *Computers and Chemistry,* vol. 26, pp. 51-56, 2001.

[15] G. Dutta, P. Jha, A. K. Laha and N. Mohan, “Artificial Neural Network Models for Forecasting Stock Price Index in the Bombay Stock Exchange,” *Journal of Emerging Market Finance,* pp. 283-296, 2006.

[16] D. Park, M. El-Sharkawi and R. Marks, “Electric Load Forecasting Using An Artificial Neural Network,” *Transactions on Power Systems,* vol. 6, no. 2, pp. 442-450, 1991.

[17] I. Basher and M. Hajmeer, "Artificial Neural Networks: Fundamentals, Computing, Design, and Application," *Journal of Microbiological Methods,* vol. 43, pp. 3-31, 2000.

[18] M. Tkác and R. Verner, "Artificial Neural Networks in Business: Two Decades of Research," *Applied Soft Computing,* vol. 38, pp. 788-804, 2015.

[19] B. Fritzke, "Growing Cell Structures - A Self-Organizing Network for Unsupervised and Supervised Learning," *Neural Networks,* vol. 7, no. 9, pp. 1441-1460, 1994.

[20] D. Specht, "Probabilistic Neural Networks," *Neural Networks,* vol. 3, pp. 109-118, 1990.

[21] J. Kamruzzaman and R. Sarker, "Forecasting of Currency Exchange Rates Using ANN: A Case Study," *IEEE Xplore,* pp. 1-6, 2004.

[22] H. Pan, C. Tilakaratne and J. Yearwood, "Predicting Australian Stock Market Index Using Neural Networks Exploiting Dynamical Swings and Intermarket Influences," *Journal of Research and Practice in Information Technology,* vol. 37, no. 1, pp. 43-56, February 2005.

[23] T. Kozdraj, "Using Artificial Neural Networks To Predict Stock Prices," *Folia Oeconomica,* vol. 225, pp. 280-294, 2009.

[24] M. Shah, N. Prabhu and J. Rao, "Performance Analysis of Neural Network Algorithms on Stock Market Forecasting," *International Journal of Engineering and Computer Science,* vol. 3, no. 9, pp. 8347-8352, September 2014.

[25] Y. Kara, M. A. Boyacioglu and O. K. Baykan, "Predicting Direction of Stock Price Index Movement Using Artificial Neural Networks and Support Vector Machines: The Sample of the Istanbul Stock Exchange," *Expert Systems with Applications,* vol. 38, pp. 5311-5321, May 2011.

[26] R. Gandhe and M. Chaudhari, "Performance Analysis of Stock Market Prediction Techniques," *International Journal of Computer Science & Communication Networks,* vol. 6, no. 1, pp. 13-17, 2016.

[27] H. Xie, X. Deng, J. Cao and F. Wang, "Empirical Analysis: Stock Market Prediction Via Extreme Learning Machine," *Neural Computing and Applications,* pp. 1-13, 2014.

[28] A. Kar, "Stock Prediction using Artificial Neural Networks".

[29] L. Falat and L. Pancikova, "Quantitative Modelling in Economics with Advanced Artificial Neural Networks," *Procedia Economics and Finance,* vol. 34, pp. 194-201, 2015.

[30] B. Vika, K. Sevrani and I. Vika, "The Usefulness of Artificial Neural Networks in Forecasting Exchagne Rates," *Academic Journal of Interdisciplinary Studies,* vol. 5, no. 1, pp. 73-81, March 2016.

[31] D. Millevik and M. Wang, "Stock Forecasting Using Artificial Neural Networks," KTH Vetenskap Och Konst, Stockholm, 2015.

[32] A. Jabbarzadeh, S. Shavvalpour, H. Khanjarpanah and D. Dourvash, "A Multiple-Criteria Approach for Forecasting Stock Price Direction: Nonlinear Probability Models with Application in S&P 500Index," *International Journal of Applied Engineering Research,* vol. 11, no. 6, pp. 3870-3878, 2016.

[33] Q. Liao, "The Stock Price Crash Risk Prediction by Neural Network," *Accounting and Finance Research,* vol. 5, no. 2, pp. 61-71, 2016.

[34] Y. Shynkevich, T. McGinnity, S. Coleman and A. Belatreche, "Predicting Stock Price Movements Based on Different Categories of News Articles," *IEEE Symposium Series on Computational Intelligence,* pp. 704-712, 2015.

[35] L. Schulze-Roebbecke, "Using Artificial Neural Networks to Generate Trading Signals for Crude Oil, Copper and Gold Futures," Management from the NOVA – School of Business and Economics, Portugal, 2016.

[36] R. Dash and P. Dash, "A Hybrid Stock Trading Framework Integrating Technical Analysis with Machine Learning Techniques," *The Jounral of Finance and Data Science,* pp. 1-25, March 2016.

[37] I. Kaastra and M. Boyd, "Designing a Neural Network for Forecasting Financial and Economic Time Series," *Neurocomputer,* vol. 10, pp. 215-236, 1996.

[38] M. H. Beale, M. Hagan and H. Demuth, Neural Network Toolbox Reference, Natick, Massachusetts: The MathWorks, Inc., 2016.

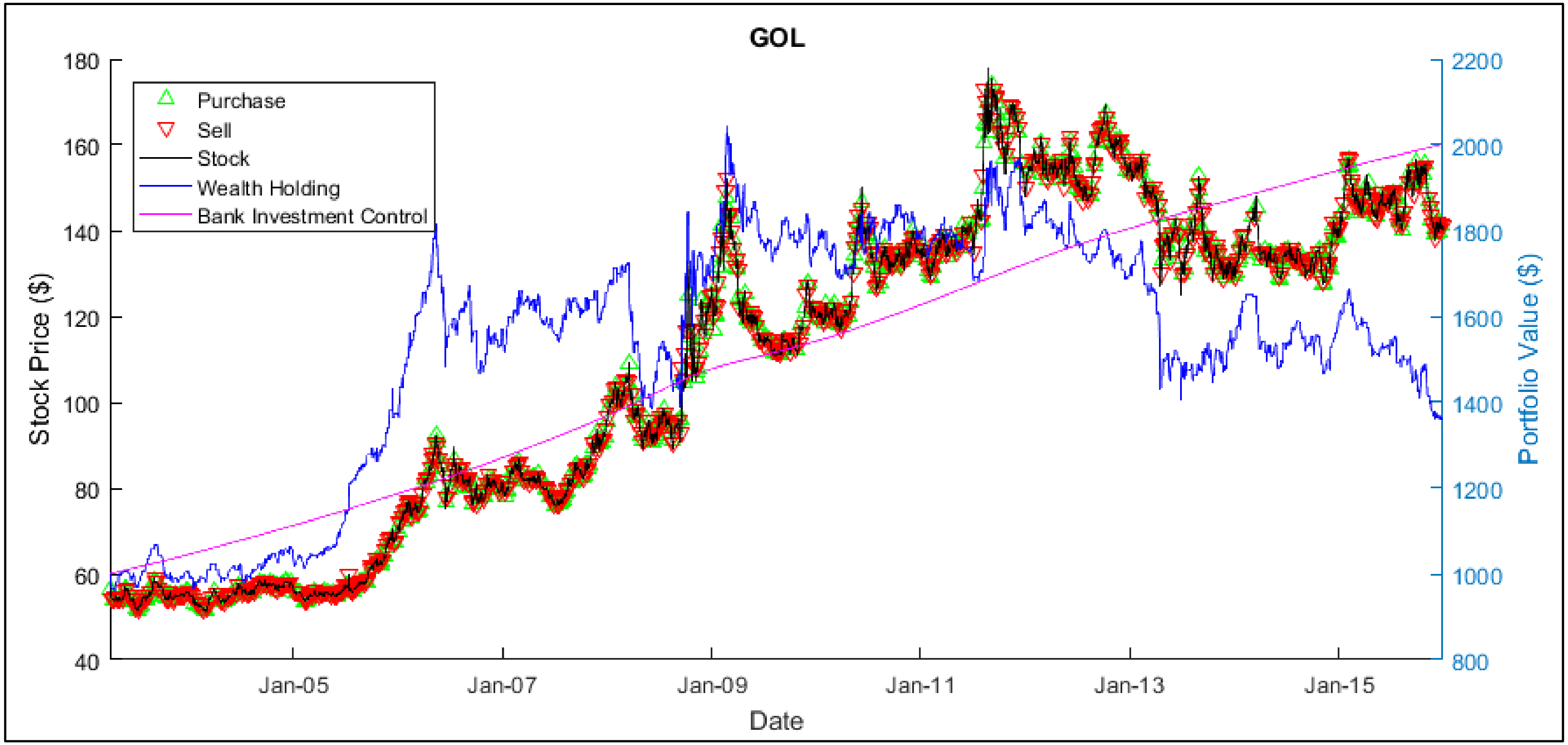
[39] D. Britz, "Wildml," AI, DEEP LEARNING, NLP, 17 September 2015. [Online]. Available: http://www.wildml.com/2015/09/recurrent-neural-networks-tutorial-part-1-introduction-to-rnns/. [Accessed 5 October 2016].

Appendix

Appendix A depicts price predictions performance when trading gold, it is in reference to Chapter 5, Section 2.1. Appendix B outlines that there is no direct trend between good trades and profit, something of note, but not great importance in this body of work. Appendix C, evaluates individual stock performance for all stocks and trading strategies, overlaying quartile performance and spread. Appendix D provides the output for CBA, by each trading strategy. It depicts the performance of each method over the trading period. Appendix E is a link to assess all raw data and graph if individual analysis is desired.

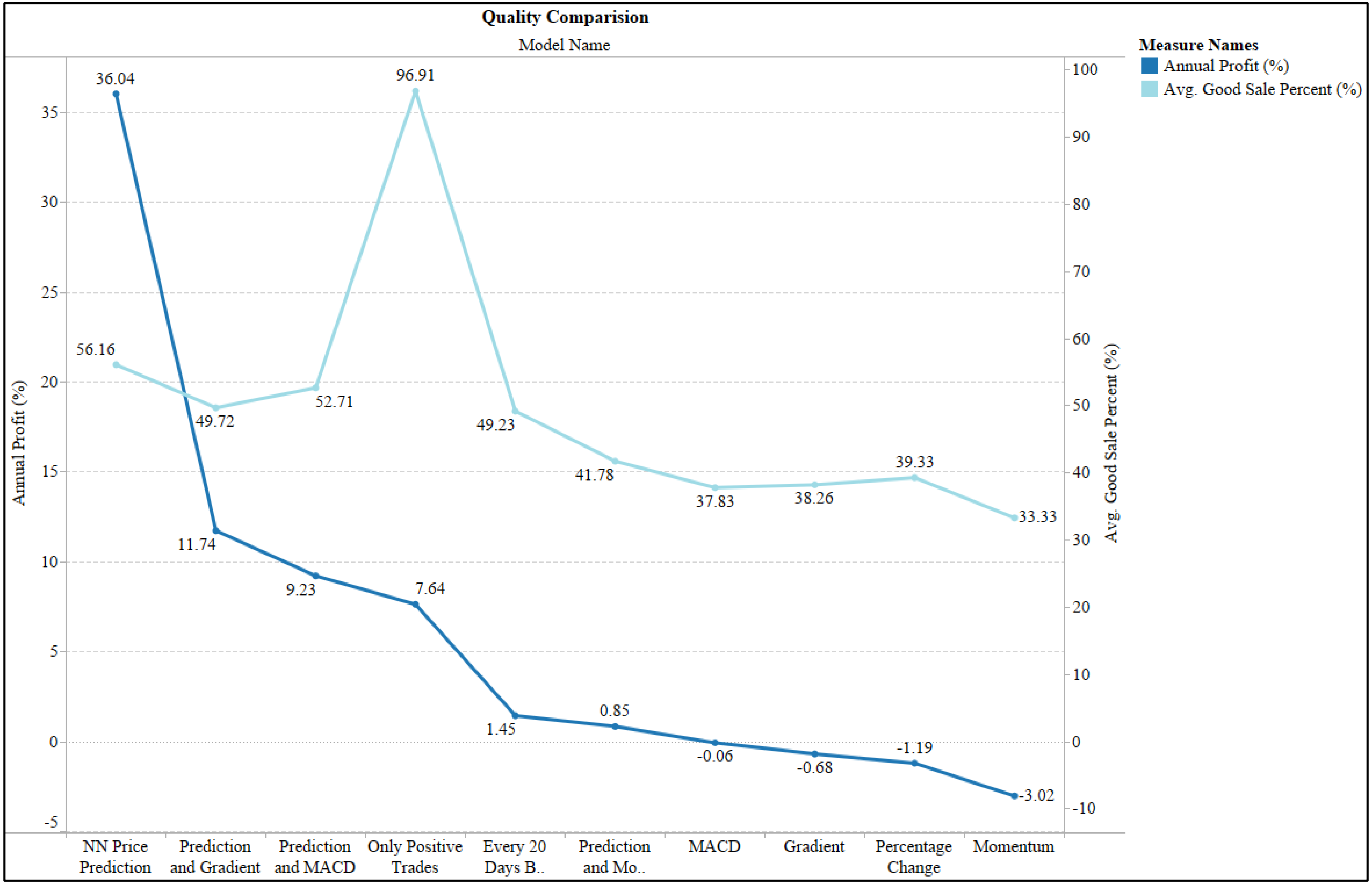
1 Appendix A

Below is pure predictions performance for Gold. Indicating its poor performance and delayed reaction



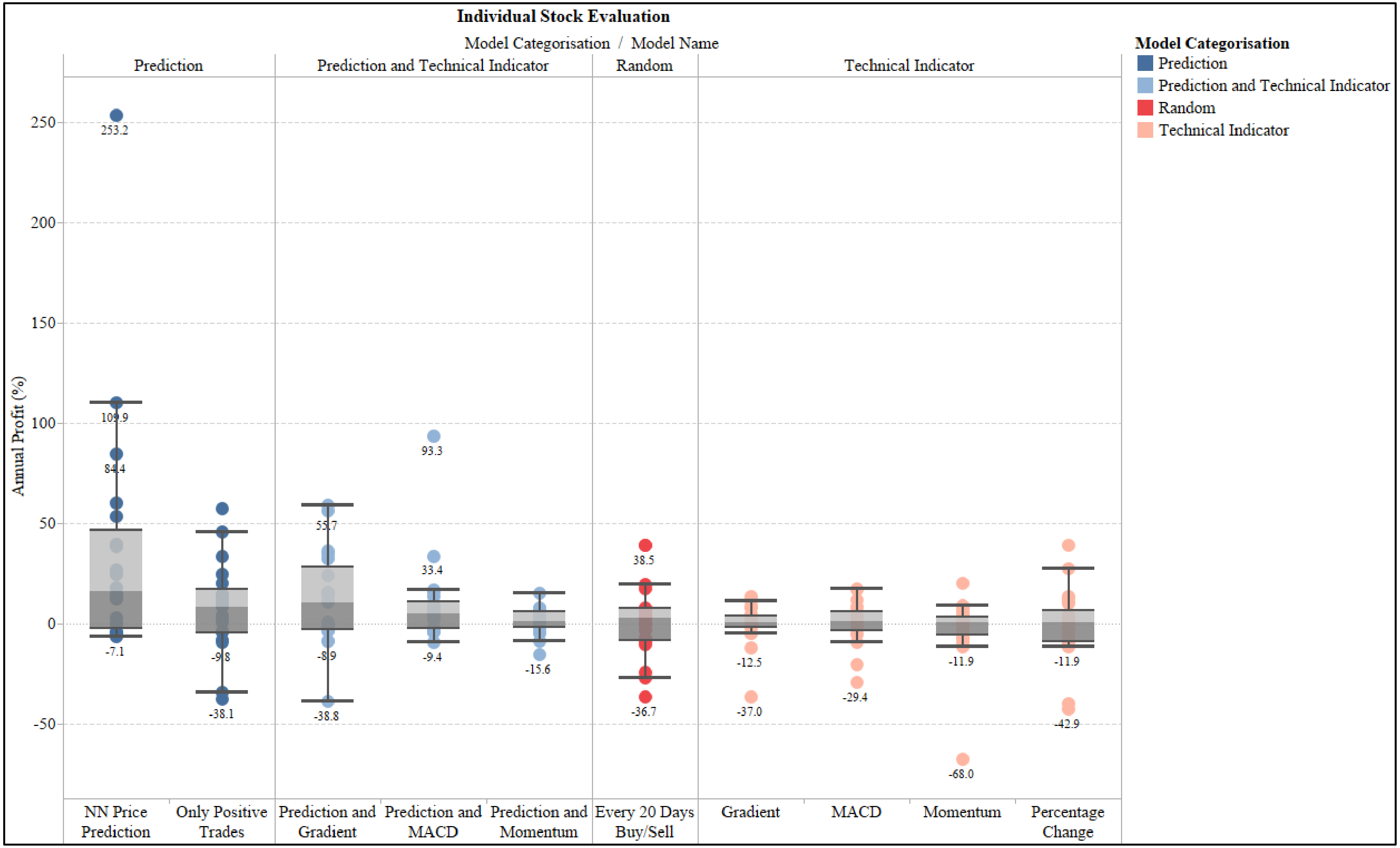
2 Appendix B

Relationship Between Good Trades and Profit



3 Appendix C

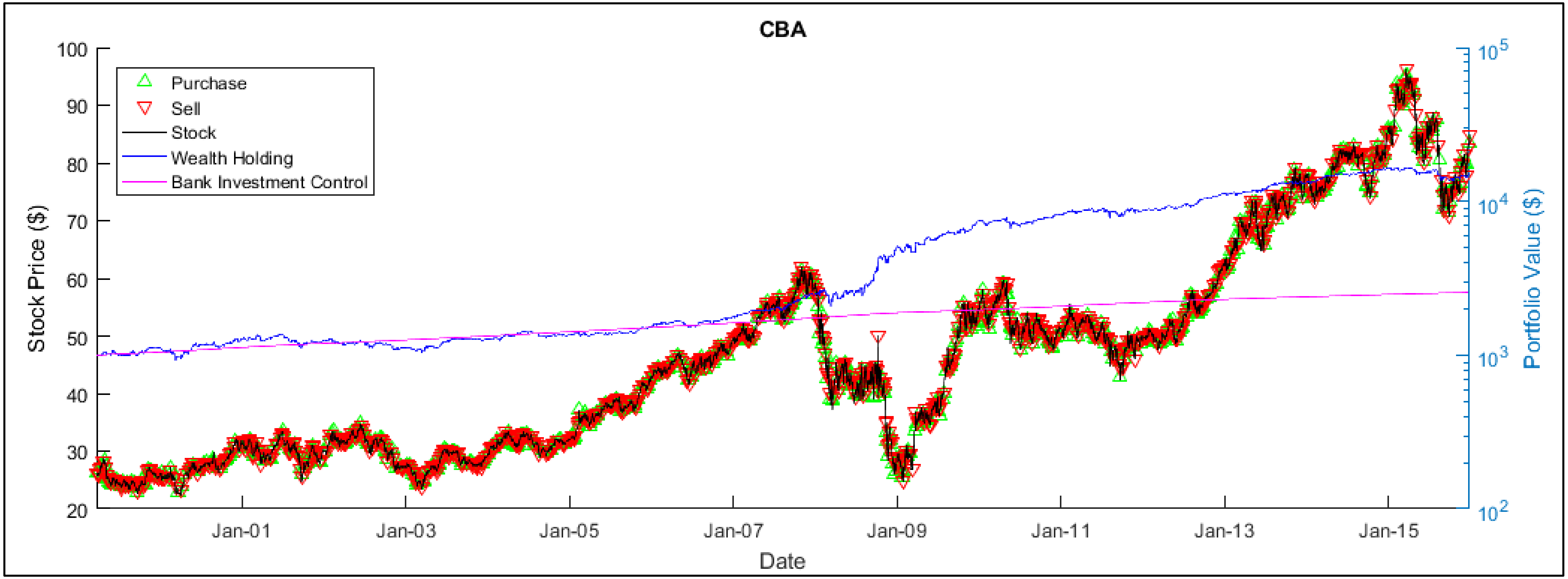
Evaluation of Each Individual Stock



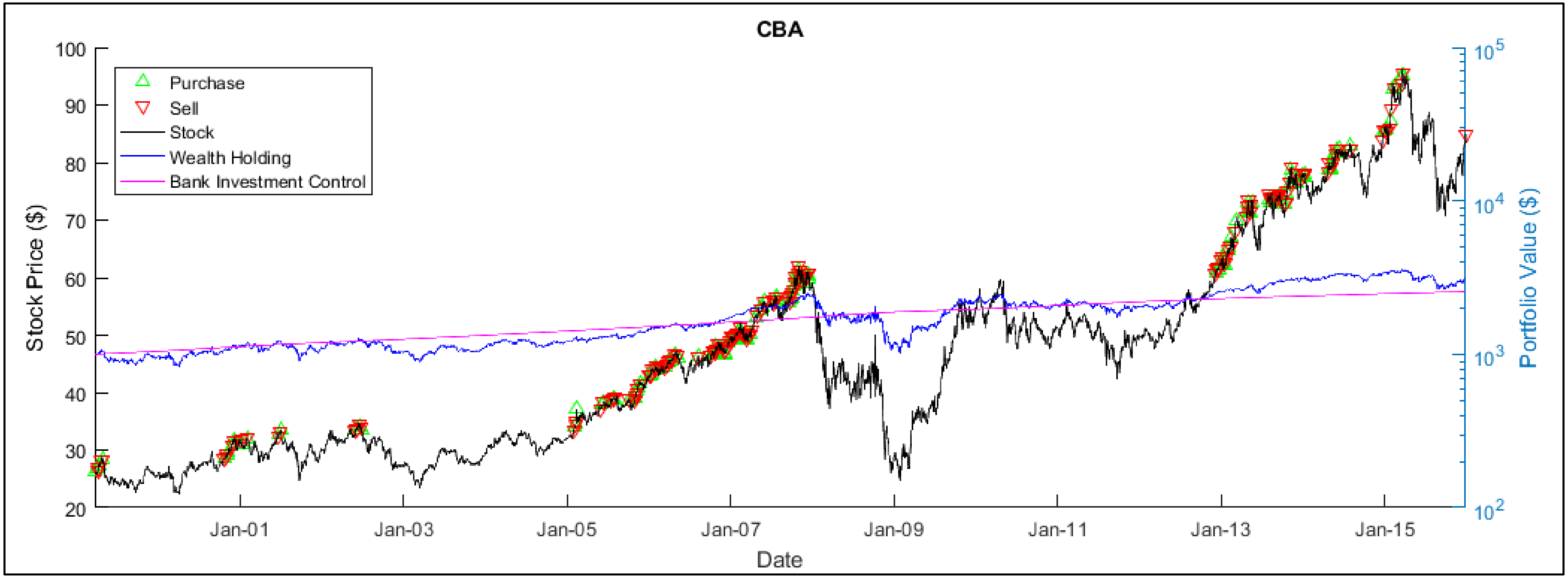
4 Appendix D

The following is the stock simulation for CBA, depicting each decision methods trading performance.

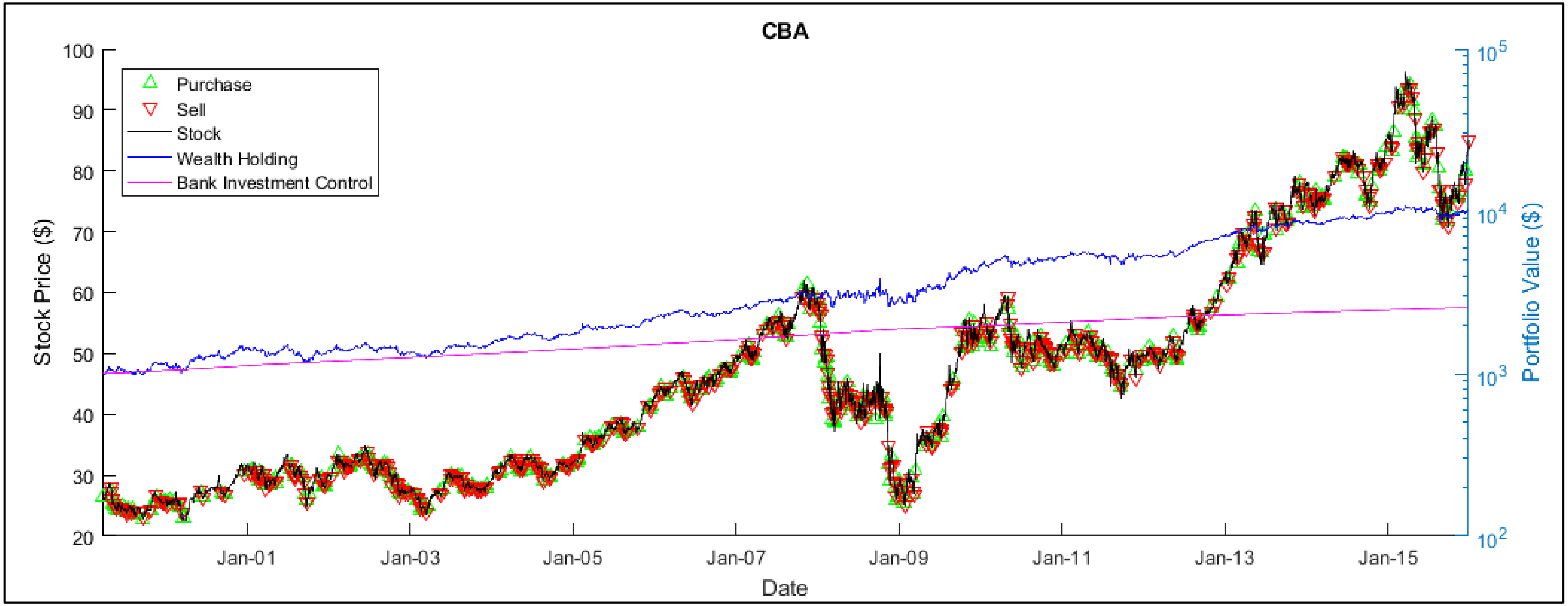
4.1 NN Price Prediction



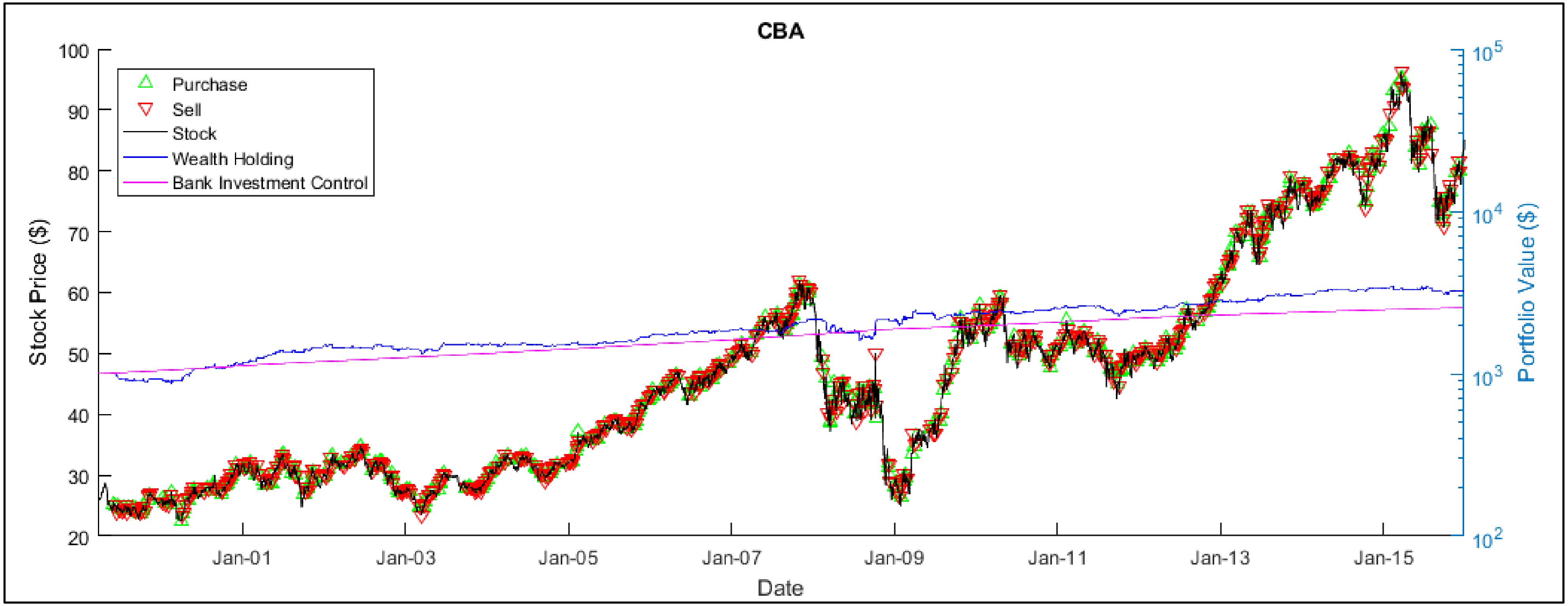
4.2 Only Positive Trades



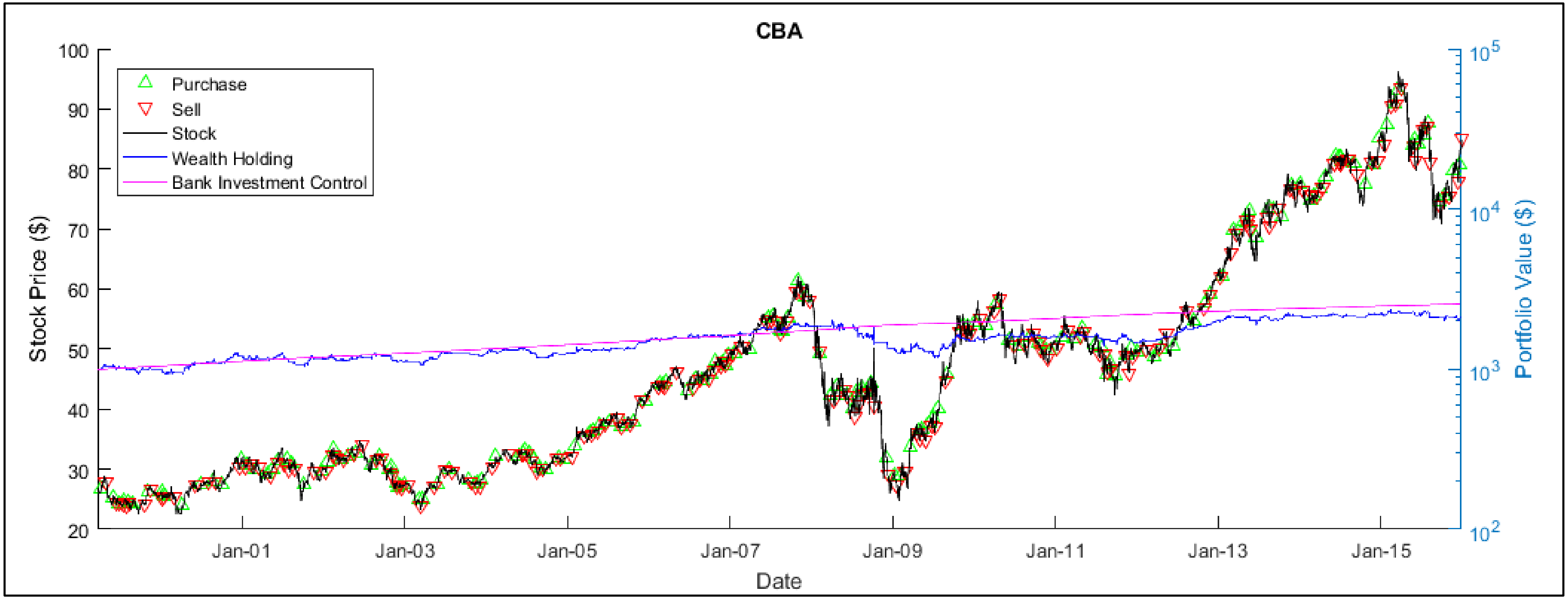
4.3 Prediction and Gradient



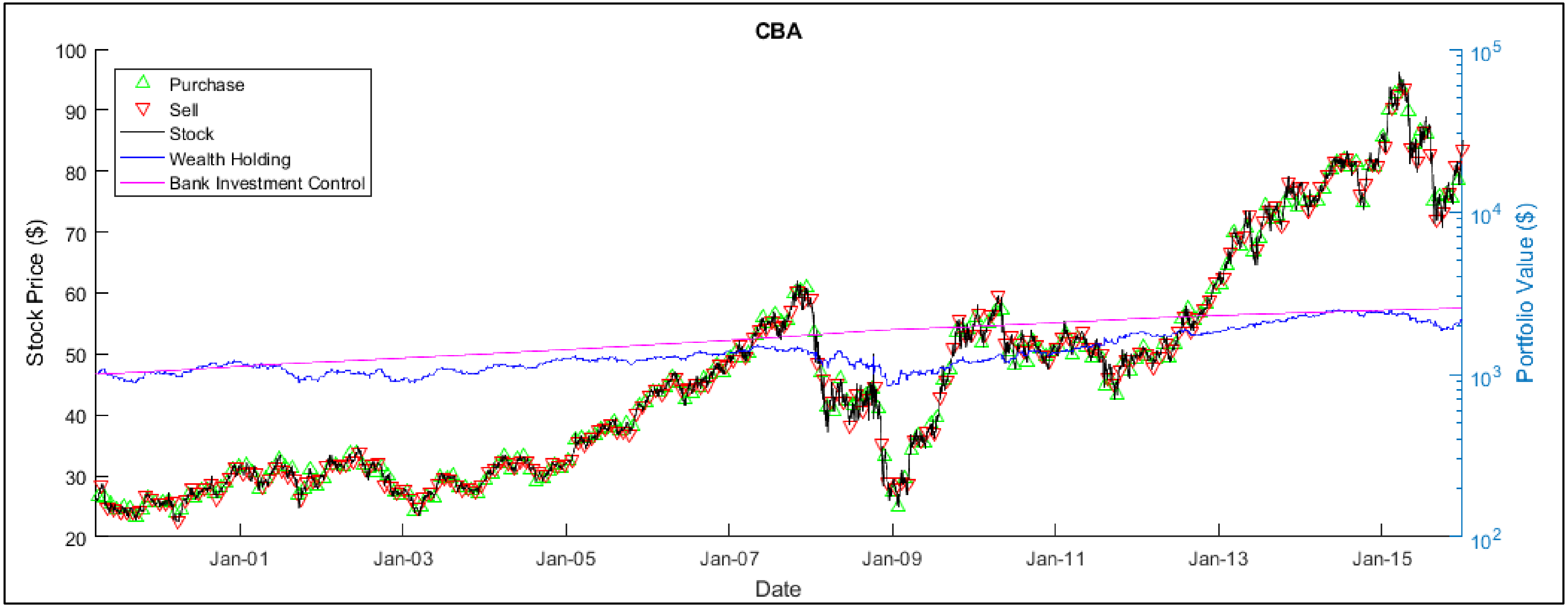
4.4 Prediction and MACD



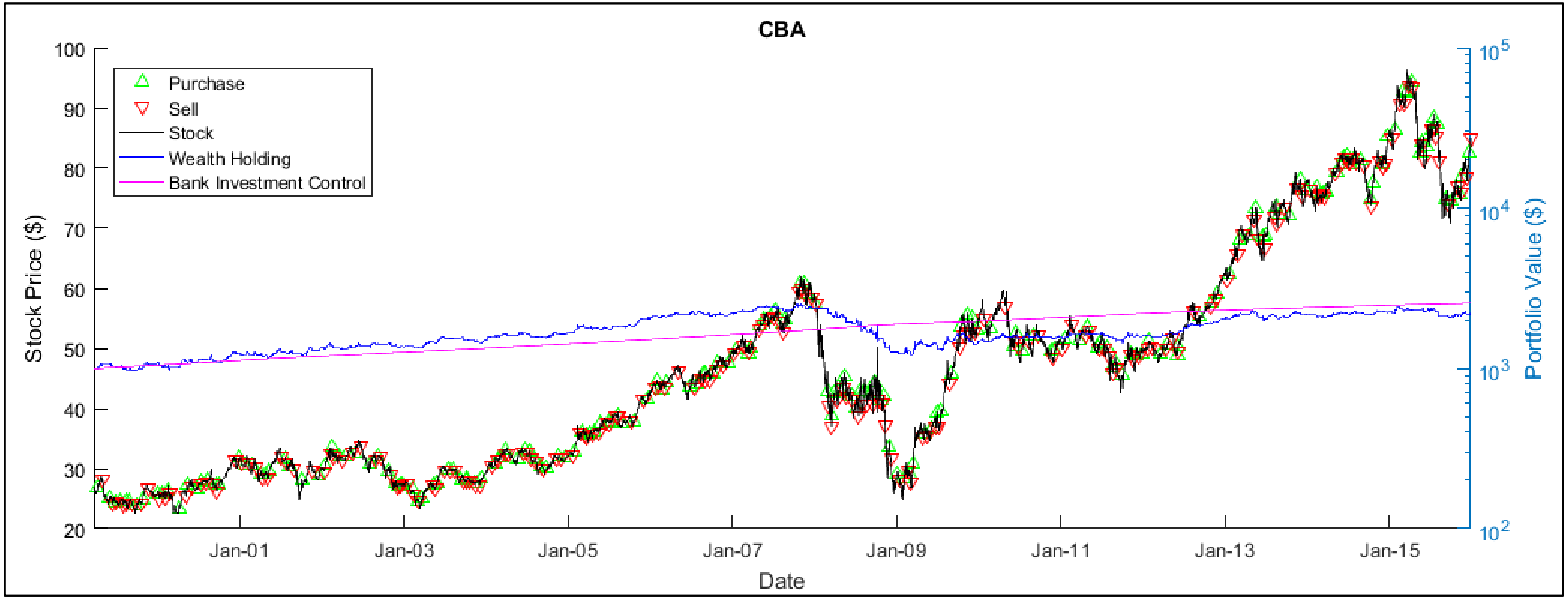
4.5 Prediction and Momentum



4.6 Every 20 Days Buy/Sell

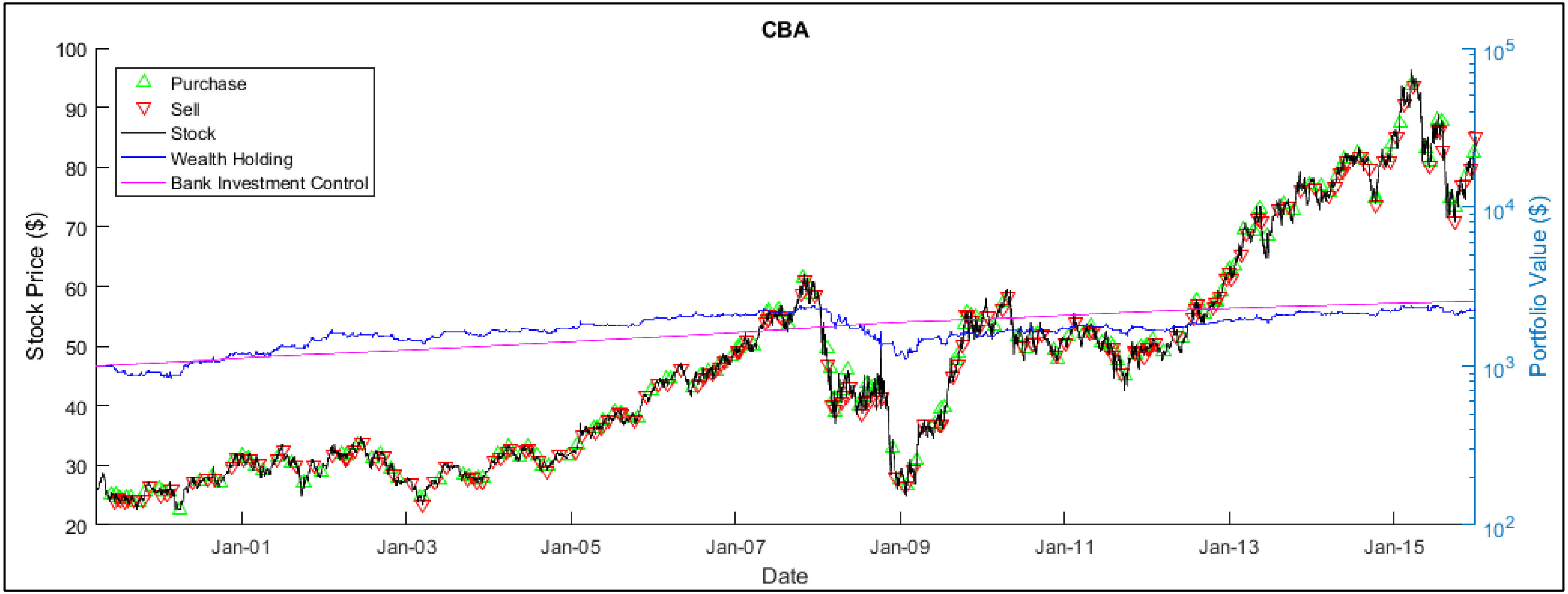


4.7 Gradient

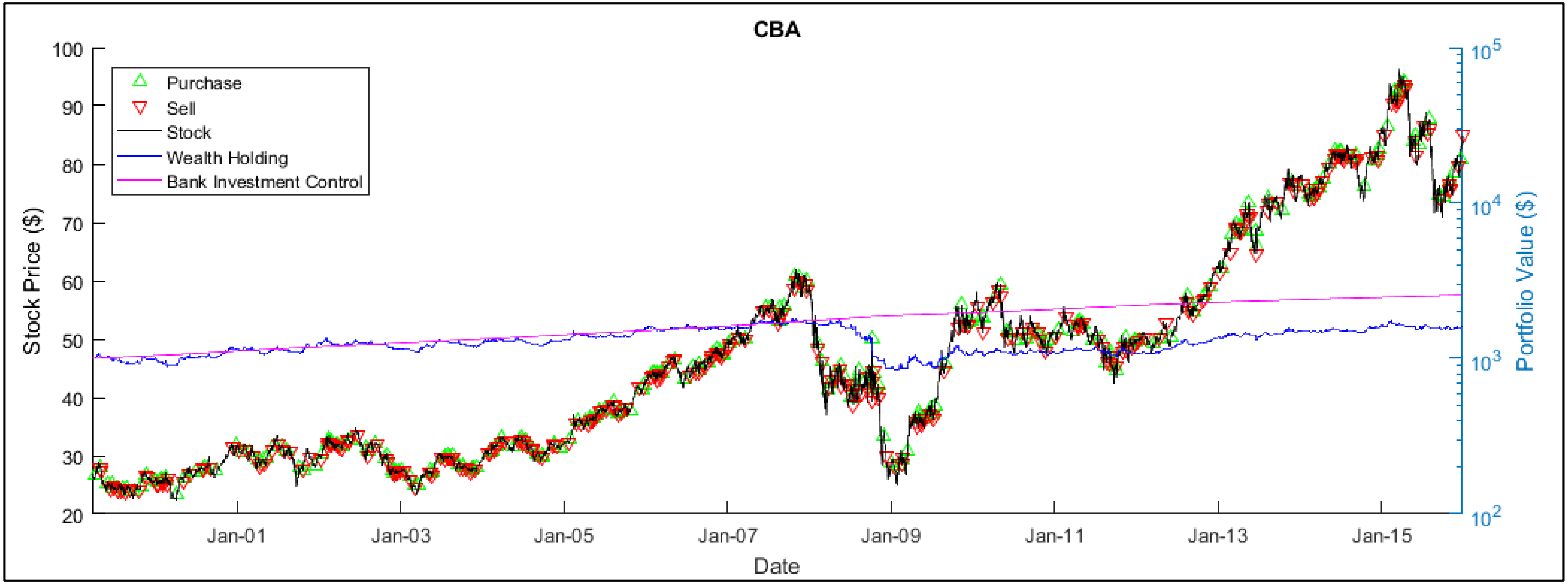

CBA
Purchase
Sell
Stock
Wealth Holding
Bank Investment Control
Stock Price ($)
100
90
80
70
60
50
40
30
20
Jan-01
Jan-03
Jan-05
Jan-07
Jan-09
Jan-11
Jan-13
Jan-15
Date
10^5
10^4
10^3
10^2
Portfolio Value ($)

4.8 MACD

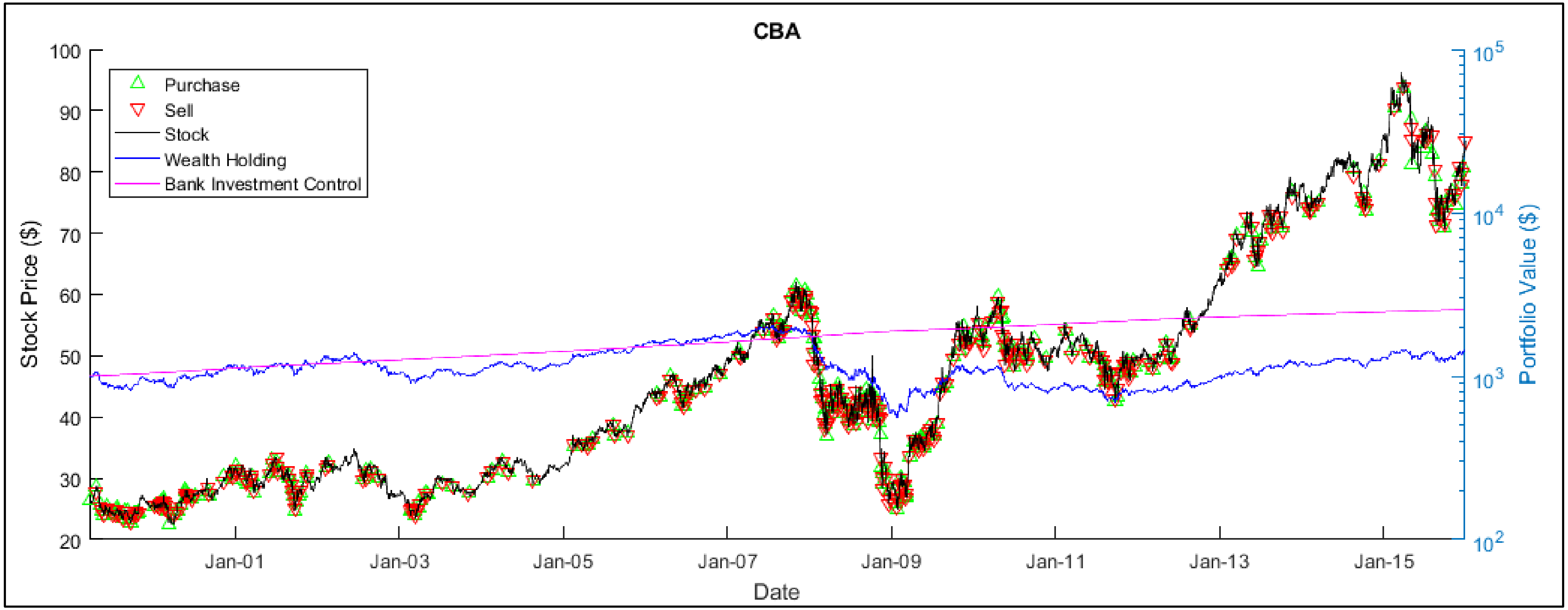
m


CBA
Purchase
Sell
Stock
Wealth Holding
Bank Investment Control
Stock Price ($)
Portfolio Value ($)
Date
100
90
80
70
60
50
40
30
20
10^5
10^4
10^3
10^2
Jan-01
Jan-03
Jan-05
Jan-07
Jan-09
Jan-11
Jan-13
Jan-15

4.9 Momentum


CBA
Purchase
Sell
Stock
Wealth Holding
Bank Investment Control
Stock Price ($)
Portfolio Value ($)
Date
100
90
80
70
60
50
40
30
20
Jan-01
Jan-03
Jan-05
Jan-07
Jan-09
Jan-11
Jan-13
Jan-15
10^5
10^4
10^3
10^2

4.10 Percentage Change



5 Appendix E

5.1 Figure outputs by stock and trading strategy

The following link is to a Google Drive folder in which one will find all the output Matlab figures labelled by stock and trading strategy:

https://goo.gl/0td34N

5.2 Raw Data Output of Simulation

The following link is to a Google Spreadsheet containing the raw data collected when the full stock simulation was run.

https://goo.gl/8ooTw0