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Original article

Creating trading systems with fundamental variables and neural networks: The Aby case study

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Abstract

The development of the Financial Crisis throughout 2008 and 2009 has made many investors and fund managers question whether growth-based investment approaches have had their day. Value-based approaches built on fundamental analysis have resurfaced again. Typically, these value-based models use fundamental variables to decide between investment opportunities. In a previous work, Vanstone et al. studied a set of filters published by Aby et al. during the dot-com crash of 2000 and subsequent aftermath, and tested and benchmarked these filters in the Australian market. The Aby filters rely on 4 different fundamental variables, and use rules with specific cut-off values to determine when to enter and exit trades. These cut-off values were found to be too restrictive for the Australian markets. This paper uses a neural network methodology by Vanstone and Finnie to develop a stockmarket trading system based on these same 4 fundamental variables, and demonstrates the important role neural networks have to play within complex and noisy environments, such as that provided by the stockmarket.

Keywords: Trading systems; Neural networks; Financial trading

1. Introduction

In essence, fundamental analysis provides a framework to decide whether a company's stock represents a good investment. It does this by attempting to assess the financial health of a company, with the expectation that if a company's financial health is sound, then the company's stock should make a good investment. To perform fundamental analysis, most practitioners study fundamental variables. These variables are the underlying metrics used to measure the company's health.

Aby et al. [1,2] used four of these fundamental variables to create a stock trading filter rule. This is a rule that can be used to decide when to buy/sell stocks based on strict values for these four fundamental variables. Vanstone et al. [18] benchmarked this filter rule, and found that it was too restrictive in the Australian market. Although the logic behind using these four fundamental variables was sound, the strict cutoff values which worked well for Aby et al. in the US were not suited to the Australian marketplace. A further issue with the stocks selected by the Aby filter is that those stocks are not highly liquid, that is, they are not heavily traded, and they are generally in the lower capitalization part of the market. The objective of this paper, then, is to develop a neural network based on

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the four fundamental variables, which can be used successfully within a highly traded stock universe, such as the ASX200.

In previous works, Vanstone and Finnie [16] presented a methodology that can be used to create stockmarket trading strategies, with and without soft computing (see also [17,15]). That methodology provides guidance for determining how to select variables of influence for the trading system to be developed, how to partition data into in-sample and out-of-sample sets, how to determine ANN architecture choices, and how to correctly benchmark results both in and out of sample.

This paper demonstrates the use of that methodology to create an effective neural trading system based on the four fundamental variables used by the Aby filter.

The initial Aby filter strategy and the Artificial Neural Network (ANN) enhanced trading strategy are comprehensively benchmarked both in-sample and out-of-sample, and the superiority of the resulting ANN enhanced system is demonstrated. The overall methodology used to create ANN-based stockmarket trading systems is described in detail by Vanstone and Finnie [16], and this methodology is referred to in this paper as 'the empirical methodology'.

2. Review of literature

The four fundamental variables used by Aby et al. are P/E (price earning ratio), Book Value, ROE (return on equity), and Dividend Payout Ratio. The variables are used in a filter rule which buys stocks under the following conditions:

1. PE < 10.
2. Market Price < Book Value.
3. ROE > 12.
4. Dividend Payout Ratio < 25%.

The stock is held until the four conditions no longer apply, upon which condition it is then sold.

The four fundamental variables used by Aby et al. are not new. Each of the individual variables has a long history in academic research. As well as the early work of Benjamin Graham (well documented by Lowe [8,9]), Basu [3] investigated whether stocks with low P/E ratios earned excess returns when compared to stocks with high P/E ratios. Basu found that during the study period (April 1957–March 1971), portfolios built from low P/E stocks earned higher returns than those portfolios built from higher P/E stocks, even after adjusting returns for risk. The study concluded that there is an information content present in publicly available P/E ratios, which could offer opportunities for investors, and that this was inconsistent with the semi-strong form of the Efficient Markets Hypothesis.

Rosenberg et al. [11] presented two strategies aimed at exploiting fundamental information to increase returns. The first, the "book/price" strategy bought stocks with a high ratio of book value to market price, and sold stocks with the reverse. The second strategy, "specific return reversal" computes specific returns per stock, and relies on the observation that specific returns tend to reverse in the subsequent month. Thus, this strategy buys stocks with negative specific returns in the preceding month, exploiting this reversal. The study sourced data from Compustat, on 1400 of the largest companies, from 1980 to 1984, and stocks were priced mainly from the NYSE. The study demonstrated statistically significant results of abnormal performance for both strategies, and suggested that prices on the NYSE are inefficient.

Detailed research from Fama and French [4] surveyed the above style of anomaly detection, and concluded that if asset-pricing is rational, then size and the ratio of book value of a stock to its market value must be proxies for risk, as opposed to reflecting market inefficiency.

Lakonishok et al. [7] found that a wide range of value strategies (based on sales growth, book-to-market, cash flow, earnings, etc.) have produced higher returns, and refute Fama and French's claims that these value strategies are fundamentally riskier. Using data from end-April 1963 to end-April 1990, for the NYSE and AMEX, Lakonishok et al. find evidence that the market appears to have consistently overestimated future growth rates for glamour stocks relative to value stocks, and that the reward for fundamental risk does not explain the 10–11% higher average returns on value stocks.

Fama and French [5] responded to Lakonishok et al. by focusing on size and book-to-value, and formed portfolios of stocks partitioned by these variables from the NYSE, AMEX and NASDAQ, from 1963 to 1992. Their results demonstrated that both size and BE/ME (book-to-market equity) are related to profitability, but the found no evidence that returns respond to the book-to-market factor in earnings. They concluded that size and BE/ME are proxies for sensitivity to risk factors in returns. Their results also suggested that there is a size factor in fundamentals that might lead to a size-related factor in returns.

Later, Fama and French [6] study returns on market, value and growth portfolios for the US and twelve major EAFE countries (Europe, Australia, and the Far East). They recognize that value stocks tend to have higher returns than growth stocks, finding a difference between low B/M (book-to-market) stocks and high B/M stocks of 7.68% per year on average. They find similar value premiums when investigating earnings/price, cash flow/price and dividend/price. They find that value stocks outperform growth stocks in twelve of thirteen major markets during 1975–1995.

Readers interested in a more detailed review of fundamental variables in trading and investment should peruse Vanstone et al. [14,16].

3. Methodology

Creation of the ANNs to enhance the Aby filter involves the selection of ANN inputs, outputs, and various architecture choices. The ANN inputs are those variables used in the Aby paper (the requirement that [Market Price < Book Value] is presented to the ANN as [Book Value/Market Price]). The possible choices for the output variable and architecture are explained below, and the logic behind those choices is well documented in the author's empirical methodology paper.

For each of the strategies created, an extensive in-sample and out-of-sample benchmarking process is used, again, this is described in detail in the authors methodology paper.

This paper uses data for the ASX200 constituents of the Australian stockmarket. Data for this study was sourced from Norgate Investor Services [10]. For the in-sample data (start of trading 1994 to end of trading 2003), delisted stocks were included. For the out-of-sample data (start of trading 2004 to end of trading 2008) delisted stocks were not included. The ASX200 constituents were chosen primarily for the following reasons:

1. The ASX200 represents the major component of the Australian market, and has a high liquidity – a major issue with previous published work is that it may tend to focus on micro-cap stocks, many of which do not have enough trading volume to allow positions to be taken, and many of which have excessive bid-ask spreads.
2. This data is representative of the data which a trader will use to develop his/her own systems, and is typical of the kind of data the system will be used in for out-of-sample trading.

Software tools used in this paper include Wealth-Lab Developer, and Neuro-Lab, both products of Wealth-Lab Inc (now Fidelity) [19]. For the neural network part of this study, the data is divided into 2 portions: data from 1994 up to and including 2003 (in-sample) is used to predict known results for the out-of-sample period (from 2004 up to the end of 2008). In this study, only ordinary shares are considered.

A primary difficulty with the filter rules used in the Aby paper is that they are too restrictive, and do not generate enough trading opportunities. In previous work [13], it was found that during the period 1992–2008, after liquidity constraints were taken into consideration, only 27 trading opportunities which met the Aby requirements existed.

The approach used in this paper is to allow a neural network access to the values for each of the four fundamental variables, so that it can learn a relationship between the values of those four variables, and the expected future returns.

The neural networks built in this study were designed to produce an output signal, whose strength was proportional to expected returns in the 1 year timeframe. In essence, the stronger the signal from the neural network, the greater the expectation of a strong investment return. Signal strength was normalized between 0 and 100.

The ANNs created each have four input time-series, namely

1. P/E.
2. Book Value per Share/Market Price per Share.
3. ROE.
4. Dividend Payout Ratio.

Outliers were removed from each variable's time-series where the original filter rule depended on using a hard-cutoff value to place trades, as outliers can severely limit a neural networks ability to learn. Observations were classed as

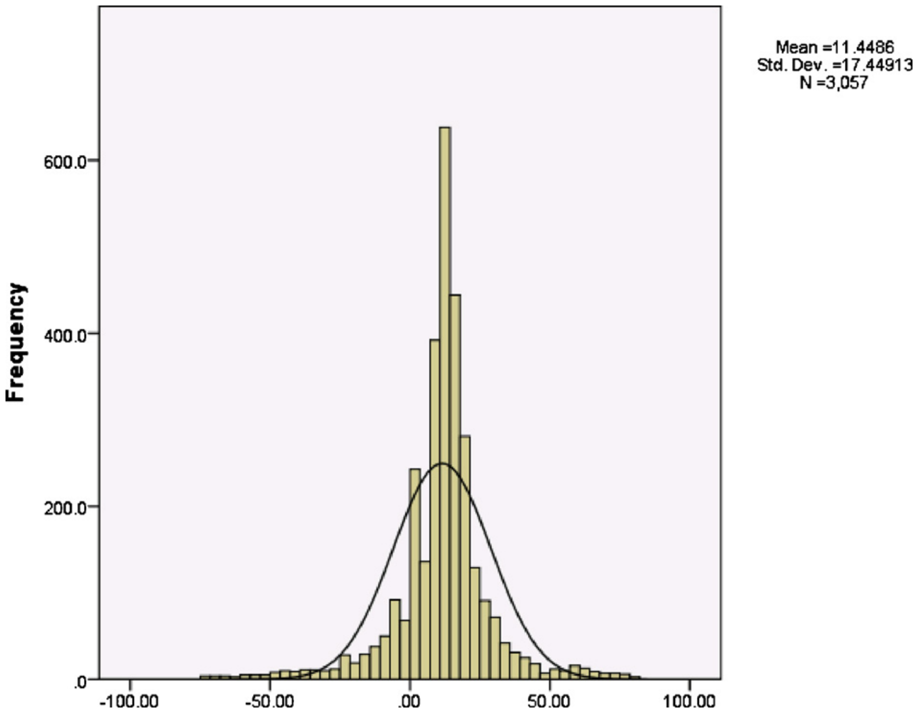

Fig. 1. P/E with outliers removed.

outliers if they lay outside the 2.5 and 97.5 percentiles. For each variable, this allowed for 95% of all value observations to be included. The variables that needed outliers removing were then P/E, ROE, and Dividend Payout Ratio. Figs. 1–3 show the key characteristics of each of these input variables after outliers have been removed.

For completeness, the characteristics of the output target to be predicted, the 200-day forward-return variable, are shown below. This target is the maximum percentage change in price over the next 200 days, computed for every element i in the input series as:

$$\frac{Highest(Close_{i+200+\cdots+i+1}) - Close_i}{Close_i} \times 100 \tag{1}$$

Effectively, this target allows the neural network to focus on the relationship between the input technical variables, and the expected forward price change. Our objective is for the neural network to learn a relationship between the four fundamental variables, and the expected forward return (Table 1).

The calculation of the return variable allows the ANN to focus on the highest amount of change that occurs in the next 200 days, which may or may not be the 200-day forward return. For example, the price may spike up after 50 days, and then decrease again, in this case, the 50-day forward price would be used. Therefore, perhaps a better description of the output variable is that it is measuring the maximum amount of price change that occurs within the next 200 days. When this amount of price change is greater than 50%, then neural network output signal is set to 100 for training purposes. Otherwise, the signal is set to 0.

As explained in the empirical methodology, a number of hidden node architectures need to be created, and each one benchmarked against the in-sample data.

Table 1
Target variable: statistical properties.

Variable	Min.	Max.	Mean	StdDev
Output	0.00	100.00	14.77	35.49

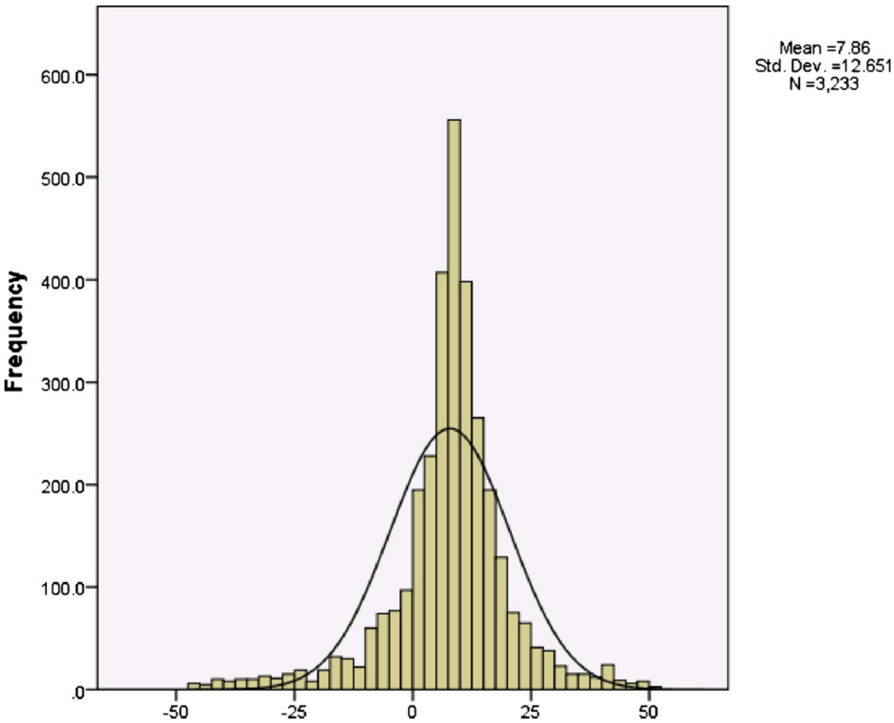

Fig. 2. ROE with outliers removed.

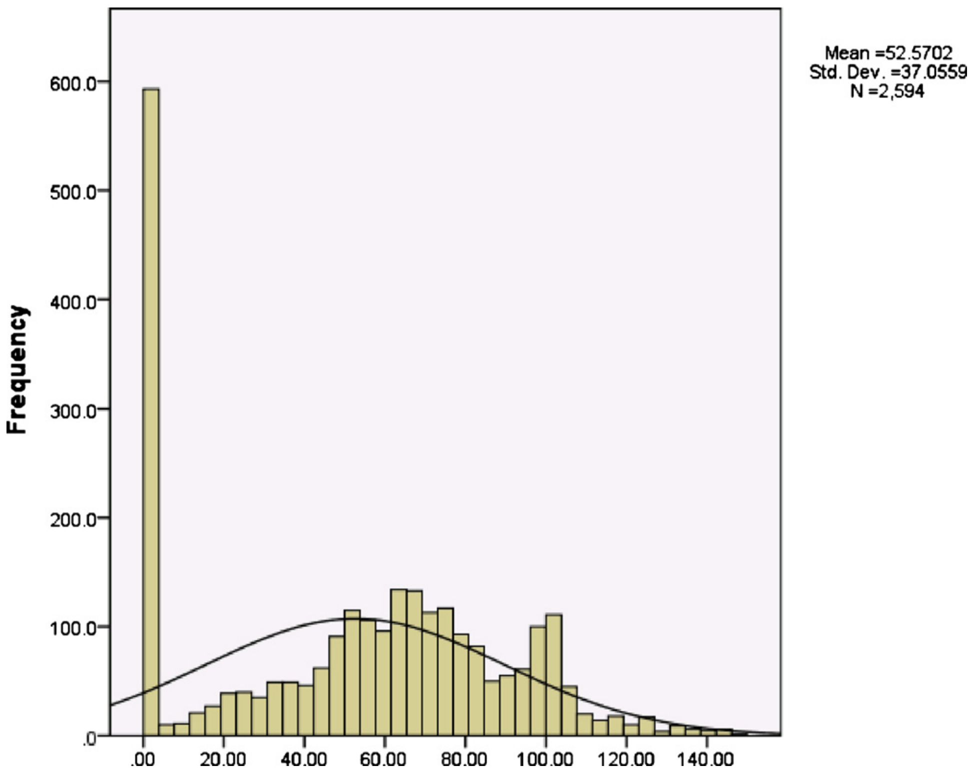

Fig. 3. Dividend Payout Ratio with outliers removed.

Table 2
In sample characteristics.

Strategy (in-sample data)	Avg. profit/day ($)	Avg. days held
Buy-and-hold naïve approach	3.78	2528
Aby filter rule	8.90	375
ANN – 2 hidden nodes (cutoff 10)	5.76	1077
ANN – 3 hidden nodes (cutoff 20)	10.16	415
ANN – 4 hidden nodes (cutoff 10)	9.54	370

The method used to determine the hidden number of nodes is described in the empirical methodology. After the initial number of hidden nodes is determined, the first ANN is created and benchmarked. The number of hidden nodes is increased by one for each new architecture then created, until in-sample testing reveals which architecture has the most suitable in-sample metrics. A number of metrics are available for this purpose, in this paper, the architectures are benchmarked using the absolute profit per bar method. This method assumes unlimited capital, takes every trade signalled, and measures how much average profit is added by each trade over its lifetime. This figure is then refined to the amount of profit added by open trades on a daily basis. The empirical methodology uses the filter selectivity metric for longer-term systems, and Tharp's expectancy [13] for shorter term systems. This paper also introduces the idea of using absolute profit per bar for medium term systems and longer term systems.

4. Results

A total of 362 securities had trading data during the test period (the ASX200 including delisted stocks), from which 8170 input rows were used for training. These were selected by sampling the available datasets, and selecting every 50th row as an input row.

Table 2 reports the profit per bar and average days held (per open trade) for the buy-and-hold naïve approach (1st row), the initial Aby filter (2nd row), and each of the in-sample ANN architectures created (subsequent rows). These figures include transaction costs of $50 each way and 0.5% slippage (as it is not always possible to get the exact price), and orders are implemented as next day market orders. There are no stops implemented in in-sample testing, as the objective is not to produce a trading system (yet), but to measure the quality of the ANN produced. Later, when an architecture has been selected, stops can be determined using ATR or Sweeney's [12] MAE technique.

The most important parameter to be chosen for in-sample testing is the signal threshold, that is, what level of forecast strength is enough to encourage the trader to open a position. This is a figure which needs to be chosen with respect to the individuals own risk appetite, and trading requirements. A low threshold will generate many signals, whilst a higher threshold will generate fewer. Setting the threshold too high will mean that trades will be signalled only rarely, too low and the traders' capital will be quickly invested, removing the opportunity to take high forecast positions as and when they occur.

For this benchmarking, an in-sample threshold of 10 is used. This figure is chosen by visual inspection of the in-sample graph in Fig. 4, which shows a breakdown of the output values of the first neural network architecture (scaled from 0 to 100) versus the average percentage returns for each network output value. The percentage returns are related to the number of days that the security is held, and these are shown as the lines on the graph. Put simply, this graph visualizes the returns expected from each output value of the network and shows how these returns per output value vary with respect to the holding period. At the forecast value of 10, the return expectation is clearly above zero in all timeframes so this value is used. Higher values would also be valid, however, care would have to be taken that there were enough trades at higher values to allow an investors capital to be placed into the market.

As described in the empirical methodology, it is necessary to choose which ANN is the 'best', and this ANN will be taken forward to out-of-sample testing. It is for this reason that the trader must choose the in-sample benchmarking metrics with care. If the ANN is properly trained, then it should continue to exhibit similar qualities out-of-sample which it already displays in-sample.

From the above table, it is clear that ANN – 3 hidden nodes should be selected. It displays a number of desirable characteristics – it extracts the highest amount of profit per bar in the least amount of time. Note that this will not necessarily make it the best ANN for a trading system. Extracting good profits in a short time period is only a desirable trait if there are enough opportunities being presented to ensure the traders capital is working efficiently.

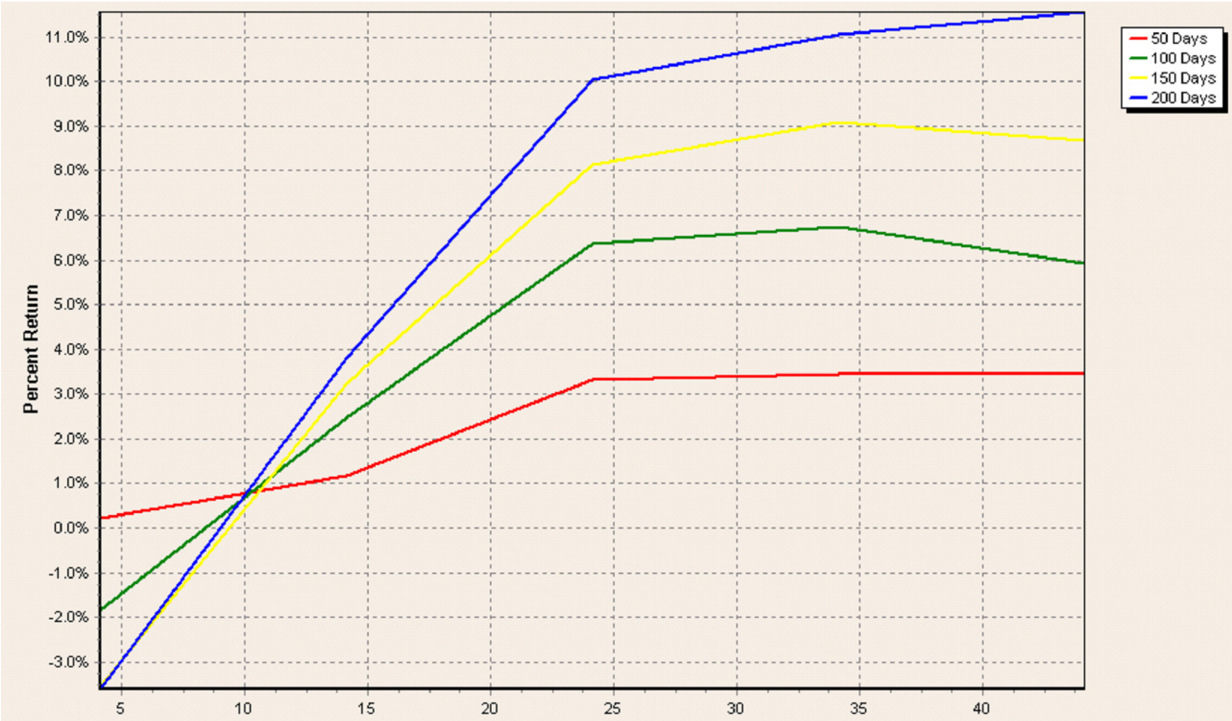

Fig. 4. In-sample ANN function profile.

Therefore, it is also important to review the number of opportunities signalled over the 10-year in-sample period. This information is shown in Table 3. Note that this table also allows for a comparison of the number of trades signalled by the original Aby approach with the number of trades signalled by the ANN based approaches. In all cases, the neural approaches have identified more opportunities.

Here the trader must decide whether the number of trades signalled meets the required trading frequency. In this case, there are likely to be enough trades to keep an end-of-day trader fully invested. There are 262 trades lasting (on average) 415 days.

This testing so far covered in-sample data previously seen by the ANN, and is a valid indication of how the ANN can be expected to perform in the future. In effect, the in-sample metrics provide a framework of the trading model this ANN should produce.

Table 4 shows the effect of testing on the out-of-sample ASX200 data, which covers the period from the start of trading in 2004 to the end of trading in 2008. These figures include transaction costs and slippage, and orders are implemented as day + 1 market orders.

Initially, this was a particularly strong bull period in the ASX200. However, this did not last, and the out-of-sample period includes the effects of the (currently ongoing) financial crisis. As such, these out-of-sample figures provide an unusual opportunity to see how this neural network trading system behaves under extremely challenging conditions.

Table 3
Number of trades signalled.

Strategy (in-sample data)	Number of trades signalled
Buy-and-hold naïve approach	362
Aby filters alone	13
ANN – 2 hidden nodes	466
ANN – 3 hidden nodes	262
ANN – 4 hidden nodes	370

Table 4
Out of sample performance.

Strategy (out-of-sample data)	Avg. profit/day ($)	Number of trades	Avg. days held
Buy-and-hold naïve approach	0.96	1	1265
Aby filters alone	18.83	1	252
ANN – 3 hidden nodes	19.86	38	390

At this stage, we would normally use the ANOVA test to quantify the differences in utility between the original Aby filter system, and the ANN based version. Clearly, however, it is pointless to do so, as the Aby filter only produced 1 trade out-of-sample. This is in line with initial expectations as when the original approach was benchmarked in-sample it only produced 13 trades over a 10-year timeframe.

One of the difficulties in attempting to quantify performance when benchmarking trading systems is the issue of overlapping trades. Although Table 4 shows 38 trades, it is likely that many of these are concurrent. From an implementation perspective, it is generally not possible to create a portfolio where all of the trades are open at the same time. This is due to the fact that if all the trades are active, only a small amount of capital can be invested in each trade. At the other extreme, if each trade starts when the previous trade ends, then all the capital can be invested in every trade.

We need to build valid portfolios to be able to measure the potential risk and return of the ANN – 3 hidden nodes strategy. To build portfolios we need to make decisions about the amount of starting capital for the portfolio, and the way we intend to invest that capital into the possible trades. The best way to do this is with a Monte-Carlo approach.

We can use Monte-Carlo simulations to create an extensive range of possible portfolios, based on the population of 38 trades, and a number of different ways of investing capital into each trade. Then we can inspect the resultant

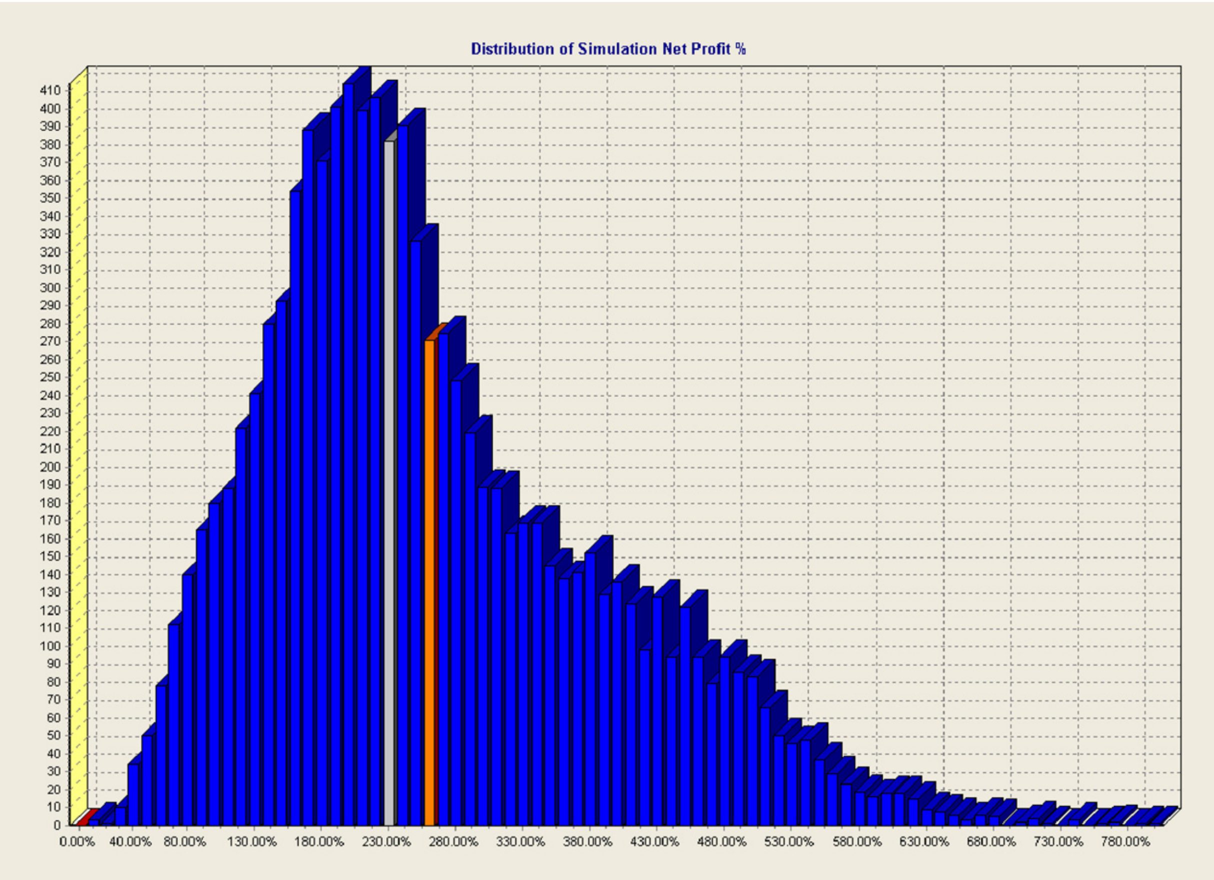

Fig. 5. Net Profit (10% equity, no volume constraints).

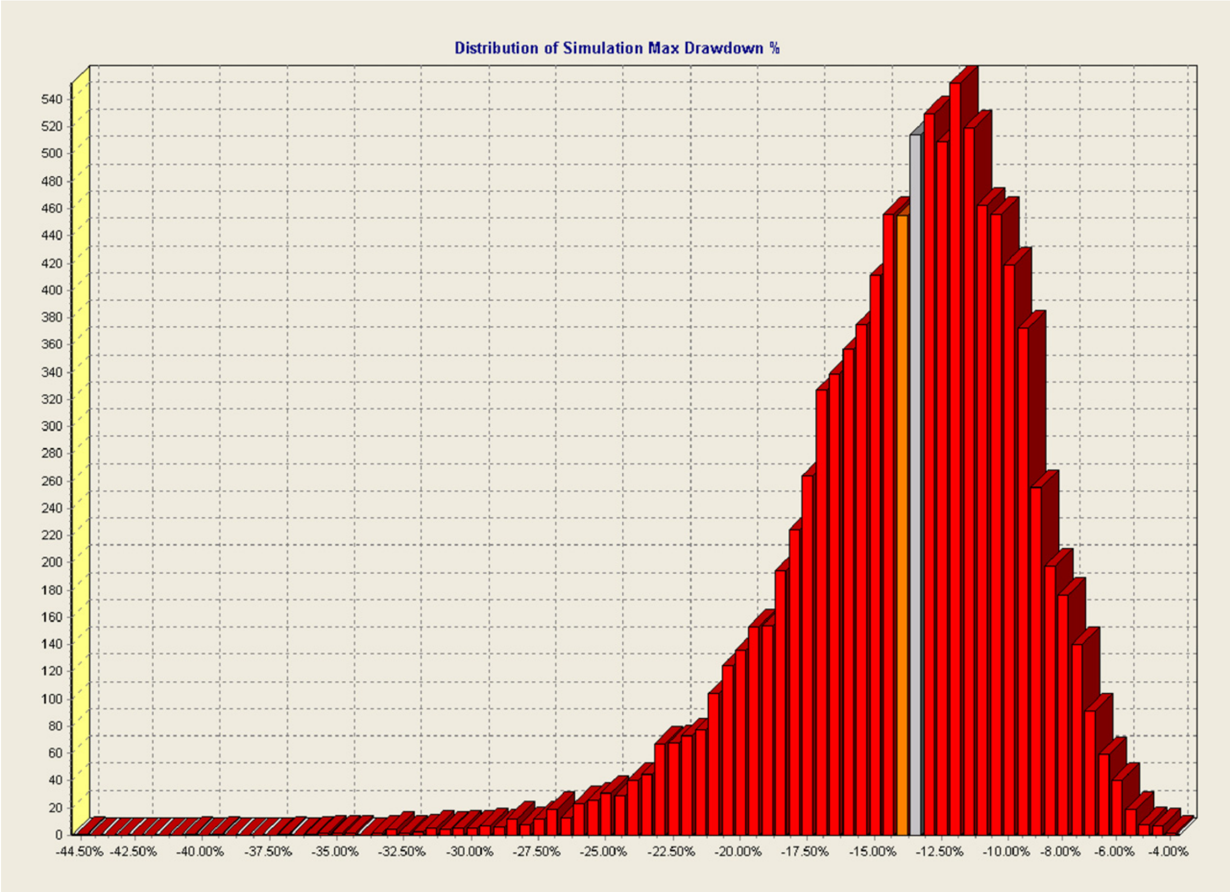

Fig. 6. Drawdown (10% equity, no volume constraints).

portfolios to determine the likely profitability and risk embedded in the trades. Further, we can use Monte-Carlo to apply volume constraints to the trades used to build the portfolios. Volume constraints allow us to ensure that the size of the trade could actually be placed in the market. For example, we cannot buy 1 million shares of a stock on a specific day, if only 500,000 were traded on that actual day. We take this into account in the backtesting simulations by constraining the number of shares to be a percentage of the actual amount of shares historically traded on the days we wish to trade in the simulation. For example, we could elect to only allow the simulation to buy up to 25% of the available stock on any given day.

In this way, the Monte-Carlo simulations can allow us to study the potential risk and return of a strategy, whilst at the same time accounting for realistic constraints of money and trade volume.

To demonstrate the value of the information that can be obtained by Monte-Carlo simulations, we create sets of possible portfolios and examine the distributions of Net Profit, and Drawdown. Net Profit is the total gross profitability over the out-of-sample time period, and drawdown as a percentage is the greatest loss experienced over that period. For example, a specific portfolio could show a Net Profit of 100% (doubled its value), but, on the way to that result, the portfolio had had a drawdown (temporary loss) of 20%. By creating the distributions for Net Profit and Drawdown, we can study the likely returns and risk inherent in the initial rules which created the trades. In this case, the trades were created using the ANN ‘3 hidden nodes’.

The next sections of this paper illustrate the outcomes of two different Monte-Carlo simulations. For the first set of simulations (Figs. 5–7), we produce the distributions for out-of-sample portfolios without trading volume constraints. Then, in the second set of simulations (Figs. 8–10), we re-create the distributions, this time with real-world trading volume constraints.

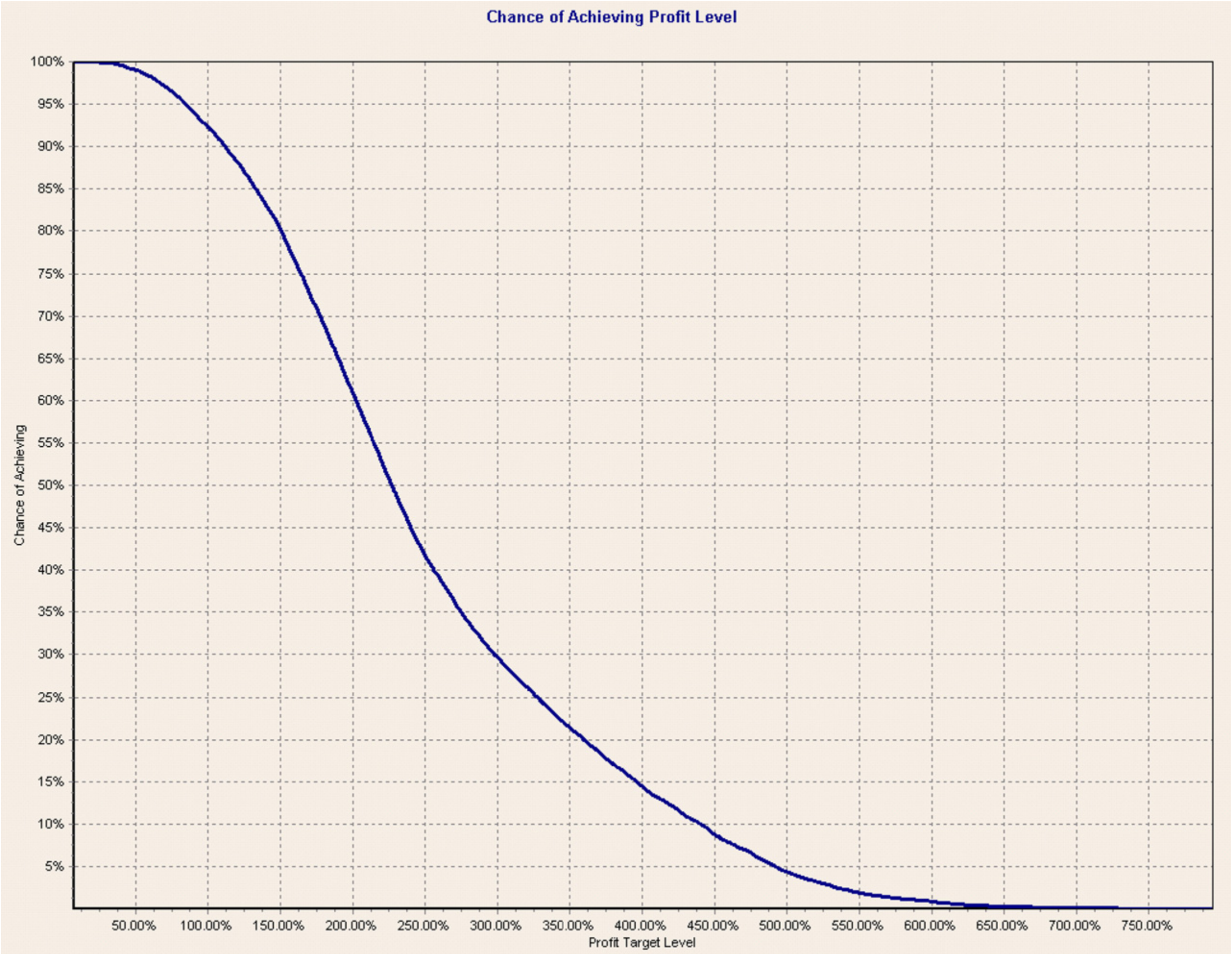

Fig. 7. Probability of achieving returns (10% equity, no volume constraints).

Fig. 5 shows the profitability effect (returns) assuming starting capital of $1 million, and investing capital using 10% of equity per trade, and Table 5 shows confidence intervals for this distribution. Fig. 6 shows the drawdown effect (risk), and Table 6 shows confidence intervals for this distribution. Finally, Fig. 7 shows the chances of achieving a specific return outcome given these distributions. This is in the form of a probability graph, which shows our probability of achieving a specific financial outcome.

These Monte-Carlo simulations were produced by creating 10,000 possible portfolio combinations resultant from these 38 trades, and measuring the gross profit and drawdown in each portfolio.

Table 5
Net profit confidence intervals (10% equity, no volume constraints).

Metric	Value
Average Net Profit	252.9%
Median Net Profit	226.86%
Largest Net Profit	793.92%
Largest 1% Extreme Net Profit	592.38%
Largest 5% Extreme Net Profit	491.83%
Smallest Net Profit	7.29%
Smallest 1% Extreme Net Profit	50.75%
Smallest 5% Extreme Net Profit	84.48%

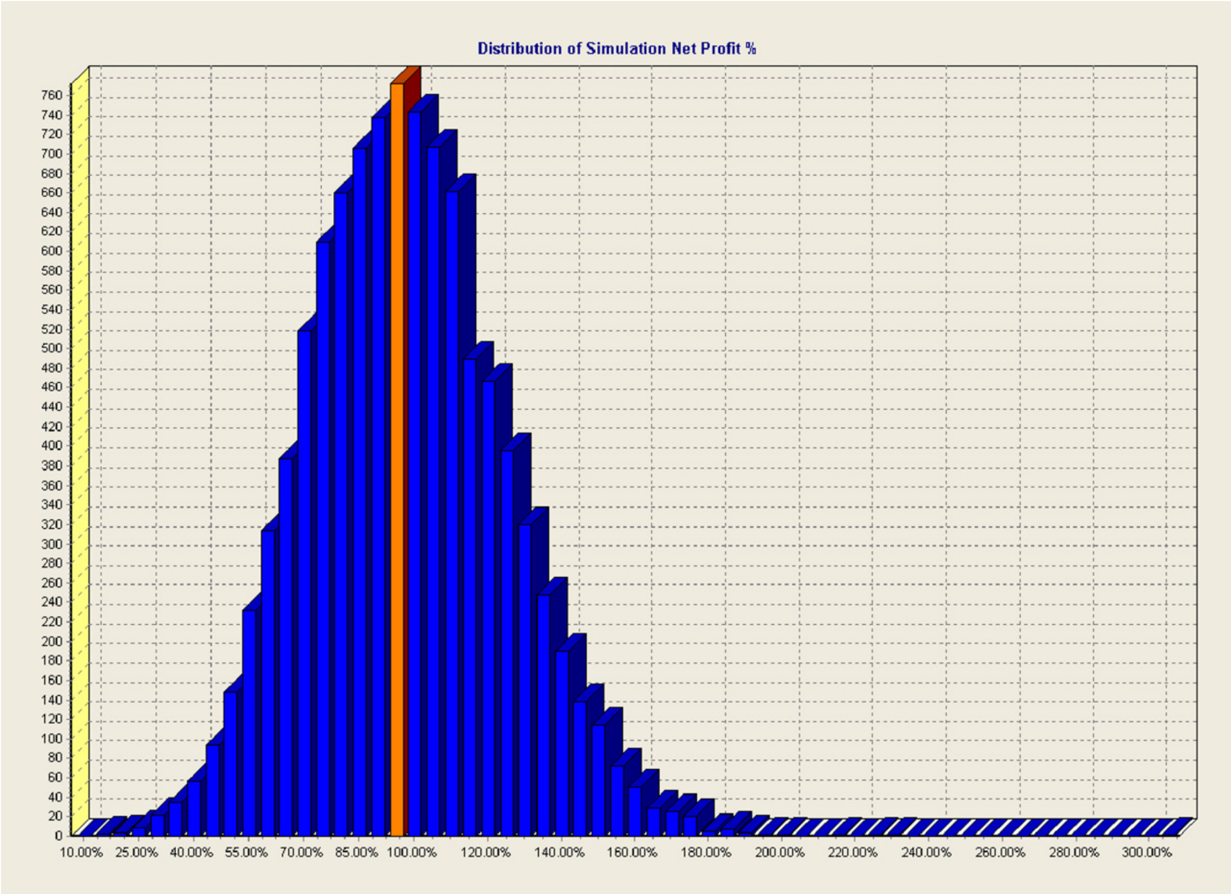

Fig. 8. Net Profit (10% equity, 25% traded volume).

Table 5 shows confidence levels for the distribution shown in Fig. 5. It reports the largest and smallest profit figures in the distribution, as well as the 1% and 5% cutoffs for each end of the distribution.

The above probability function allows us to estimate the probability of achieving a specific return outcome. For example, our probability of achieving a 100% return on $1 million is 93%, if we invest our capital at 10% of equity into each trade.

As previously mentioned, to create real world simulations, we need to constrain our investments to some specific maximum amount of the actual volume of stocks traded on the specific dates of our trades. There are many ways to determine an appropriate volume constraint. Given the high liquidity of the ASX200, constraining volume to approximately 25% of traded volume would be acceptable.

Table 6
Drawdown confidence intervals (10% equity, no volume constraints).

Metric	Value
Average Drawdown	−14.28%
Median Drawdown	−13.69%
Largest Drawdown	−44.66%
Largest 1% Extreme Drawdown	−27.12%
Largest 5% Extreme Drawdown	−22.10%
Smallest Drawdown	−4.46%
Smallest 1% Extreme Drawdown	−6.73%
Smallest 5% Extreme Drawdown	−8.40%

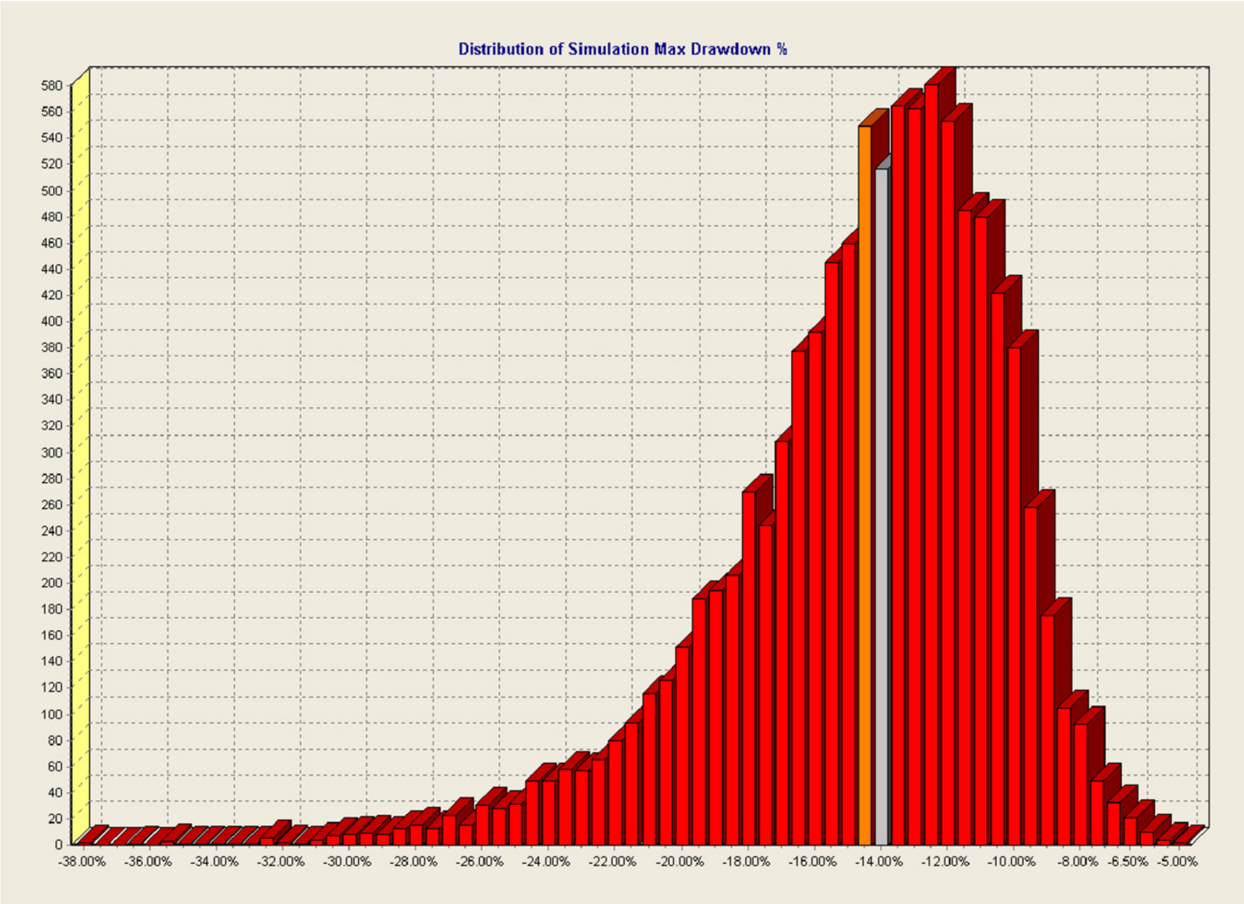

Fig. 9. Drawdown (10% equity, 25% traded volume).

To assess our returns and risk with a volume constraint of 25% of traded volume, we can again produce the required Monte-Carlo distributions. These are presented as Figs. 8–10, and Tables 7 and 8.

Monte-Carlo simulations add a great deal of depth when assessing trading system results. Rather than rely on the metrics produced by one unique backtest, the Monte-Carlo process allows the construction of a large numbers of possible portfolios, each created under realistic trading constraints of money and trading volume.

The Monte-Carlo simulations add a great deal of value to the study of the potential of the neural strategy. From comparing the probability graphs in Figs. 7 and 10, the simple addition of a sensible 25% constraint on trading volume changes our likelihood of achieving 100% profit from approximately 93% to approximately 39%. It is also apparent

Table 7
Net profit confidence intervals (10% equity, 25% traded volume).

Metric	Value
Average Net Profit	94.04%
Median Net Profit	93.15%
Largest Net Profit	300.15%
Largest 1% Extreme Net Profit	159.51%
Largest 5% Extreme Net Profit	139.07%
Smallest Net Profit	13.25%
Smallest 1% Extreme Net Profit	37.31%
Smallest 5% Extreme Net Profit	52.89%

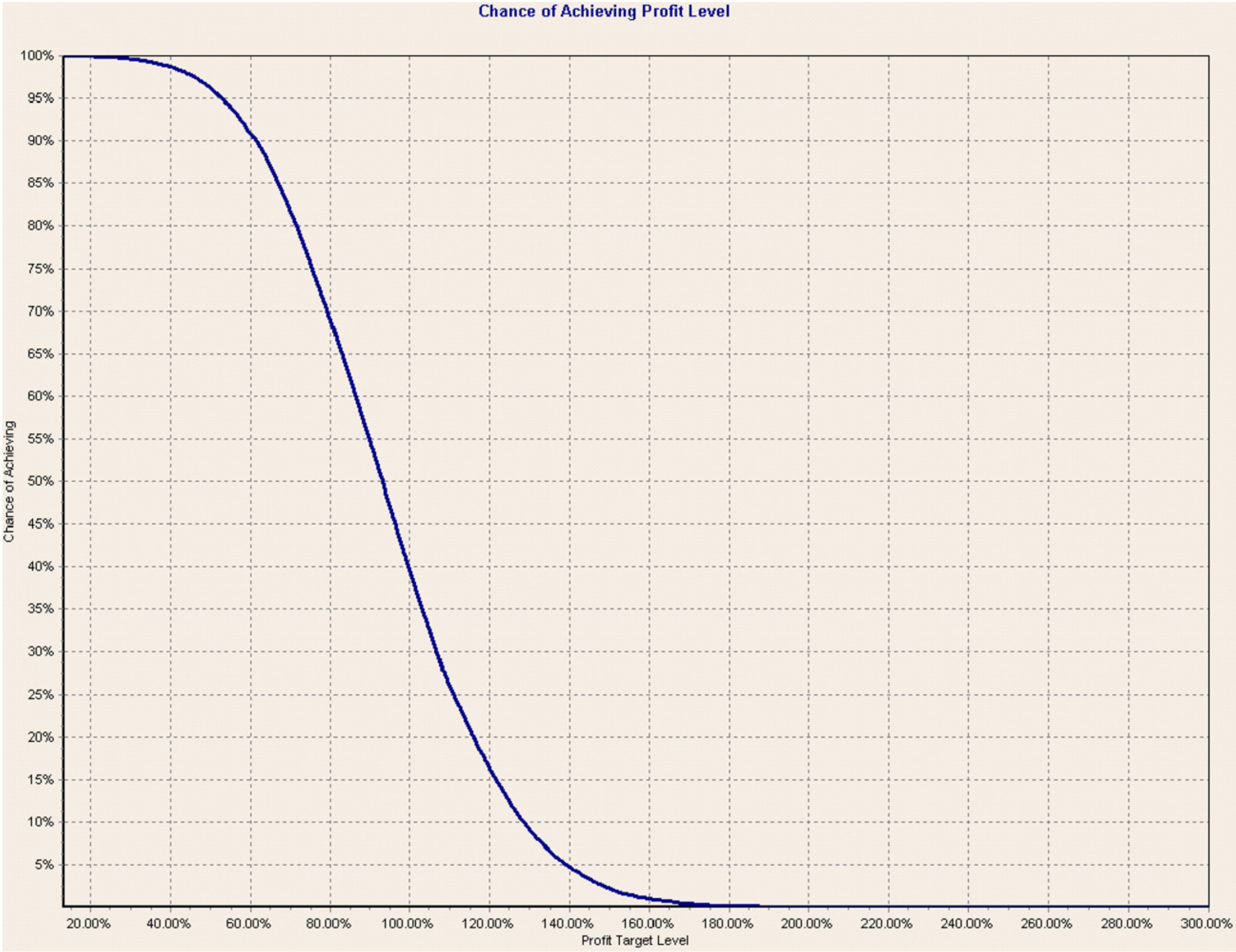

Fig. 10. Probability of achieving returns (10% equity, 25% traded volume).

Table 8
Drawdown confidence intervals (10% equity, 25% traded volume).

Metric	Value
Average Drawdown	−14.85%
Median Drawdown	−14.21%
Largest Drawdown	−38.19%
Largest 1% Extreme Drawdown	−27.39%
Largest 5% Extreme Drawdown	−22.54%
Smallest Drawdown	−5.01%
Smallest 1% Extreme Drawdown	−7.80%
Smallest 5% Extreme Drawdown	9.52%

from the additional Monte-Carlo study that the returns and risk embedded in the trades selected by the ANN are materially dependant on the size of the trades executed.

5. Conclusions

From this data presented above, it is clear that the ANN has gone some significant way towards meeting its objectives. It has certainly performed extremely well in terms of its profitability, as it was trained to do. However, the Monte-Carlo distributions also clearly show that the returns of the strategy are very volatile.

There may be at least two reasons for this. Firstly, the ongoing Financial Crisis has had a huge impact on the volatility of equity returns around the world. The out-of-sample returns certainly reflect this reality. Secondly, the 4 variables used in both the Aby filter and the ANN-base approach are all fundamental variables. They focus on the internal financial characteristics of a company, but not on the current state of the market.

Further work needs to be done to allow the ANN access to some variables that describe the current state of the market. A suggested neural network input for future work would be the moving average of the market index. This would allow the ANN access to information describing the state of the market as a whole, which would provide valuable timing information to the ANN.

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