TRADING FOREIGN CURRENCY USING ARTIFICIAL NEURAL NETWORK STRATEGIES

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Abstract: The foreign exchange (FX) markets represent an enormous opportunity for traders. These markets have huge liquidity, trade 24 hours a day (except weekends), and allow the use of leverage. This paper takes a simple FX trading strategy and shows how to substantially improve it, using a neural network methodology originally developed by Vanstone & Finnie for creating and enhancing stockmarket trading systems. This result demonstrates the important role neural networks have to play within complex and noisy environments, such as that provided by the intraday FX markets.

1 INTRODUCTION

The FX markets are designed to assist international trade and investment, by allowing participants to easily convert one currency into another at an agreed rate. Although this is the primary purpose of the FX markets, they also provide an outstanding opportunity for currency speculators.

The FX markets currently have a daily turnover of approximately $4 trillion (BIS, 2010). They trade 24 hours a day (except weekends) around the globe, with focus shifting between different geographical regions in accordance with the business hours of those regions.

FX markets are particularly attractive to short-term speculators due to their high liquidity, their use of leverage, and their low transaction costs. Further, there are a number of software products which allow high-frequency and intraday traders to trade the markets algorithmically. This allows these traders to exploit price changes in very small timeframes.

This paper focuses on an existing methodology for creating and enhancing trading strategies both with and without soft computing, developed by Vanstone & Finnie (Vanstone and Finnie, 2009). Using this methodology, we create a neural network to enhance a simple FX intraday breakout trading strategy. The original strategy and the ANN enhanced version are comprehensively benchmarked both in and out-of-sample, and the superiority of the ANN enhanced version is demonstrated.

2 REVIEW OF LITERATURE

Traditional financial models have difficulty explaining the gap between financial theory and practice. In theory, exchange rate determination is based on rational expectations and efficient markets, with publicly available information being the major influence on longer term price structures. However, this view leaves no role for the behavior of traders to influence market prices.

From a market microstructure point of view, research has found that trading is an important factor in the price formation process (Love and Payne, 2009), and a number of trading behaviours such as 'herd behaviour' and 'over(under)-reaction' have been documented (see, for example: (Kirman, 1995), (Carpenter and Wang, 2007), (Serban, 2010)). At short time horizons, there remains no well accepted model of exchange rate determination.

According to the Bank for International Settlements (BIS, 2010), the FX 'spot' market size is approximately $1.5 trillion and has a high turnover largely due to more active trading. This suggests that as much as 37.5% of the FX markets are being actively traded in the shorter term, even though there is no well accepted model of short term exchange rate determination.

In practice, most traders rely on Technical Analysis to make trading decisions. Technical Analysis provides a framework based on price, price movements, and price patterns. Research shows that

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nearly all traders in the FX markets use technical analysis, particularly for trading in the shorter timeframes (Cross, 1998); (Menkhoff and Taylor, 2007).

As the majority of traders in the shorter term FX markets are employing algorithmic trading models, and most base their decision frameworks on Technical Analysis, it is appropriate to select a strategy which selects trading opportunities solely based on price movement. For this reason, a simple price based strategy is used in this paper.

Breakout trading is one simple method short term traders use to capture profits in the FX market. Essentially, breakout traders wait for price to break above some previously defined threshold and they use this breakout as the signal to enter a trade.

Although many good opportunities are signaled by breakout rules, a large number of breakouts quickly fail. The difficulty for traders is to assess which breakouts are likely to continue, and which are likely to fail. This is a forecasting function, and is ideally suited to an Artificial Neural Network (ANN).

ANNs have long been used within the trading and investment community to assist with making decisions in complex, non-linear, and noisy environments. A comprehensive review of the ways that ANNs have assisted traders build profitable trading models is available in Vanstone et al (Vanstone and Tan, 2003).

3 METHODOLOGY

The most heavily traded currency in FX markets is the EURUSD pair (Euro dollar, quoted in US Dollars), which accounts for approximately 28% of the spot market (BIS, 2010), and data for this pair is used in the paper. Given the incredible turnover and importance of this currency pair, it should be one of the most ‘efficient’ securities in existence.

The software used to conduct the testing of trading strategies, and the creation of the neural networks is Wealth-Lab Developer 6 (2011).

For the neural network part of this study, the data is divided into two partitions: data from 01/01/2000 up to and including 31/12/2005 (in-sample) is used for training the networks, which are then tested over the period 01/01/2006 to 30/04/2011 (out-of-sample).

A primary difficulty with breakout strategies is determining which breakouts are likely to be sustained and hence lead to a profitable outcome, as compared to those which quickly fail and lead to an unprofitable outcome. This is the specific issue that the ANNs in this paper are designed to address.

As this paper is focused on high-frequency currency trading, the system developed is designed to be run in the 1-hourly timeframe, and aims to hold trades open for up to 12 hours. For the simple breakout system, the rule to buy (sell) is price closing above (below) the high (low) of the last 8 hours.

Creation of ANNs to enhance simple breakout trading systems involves the selection of ANN inputs, outputs and various architecture choices. Each of these areas is discussed in more detail below.

3.1 Selection of Inputs

As the final trading system is to be run in a high-frequency format, the primary choice of variables are those produced directly from price data, namely, Technical Variables. Among this group, support has been found for Moving Averages of various lengths (Preen, 2010); (Dewachter, 2001); (Levich and Thomas, 1993); (Schulmeister, 2008)), MACD ((Preen, 2010)) and Stochastics (Preen, 2010).

These variables are ideal for use within a neural network as they are easily calculated, and react immediately to changes in price. The values of these variables are sampled every hour.

The three input variables chosen and their formula are:

1. EMA(Period)

$$EMA = (K \times (C - EMA_1)) + EMA_1 \tag{1}$$

where

C = Current Price,
EMA_1 = Previous EMA value,
$K = 2 / (1 + \text{period})$

2. MACD

$$MACD = EMA(12) - EMA(26) \tag{2}$$

3. Stochastic(K,N)

$$Stochastic = SMA(StochK, N) \tag{3}$$

where
N = the smoothing period,
SMA = Simple Moving Average,
$StochK = (C-L(K)) / (H(K)-L(K))*100$,
C = closing price,
$L(K)$, $H(K)$ = the lowest low (highest high) in K periods

The statistical properties of these inputs is shown in Table 1.

Table 1: Statistical Properties of Input Variables.

Variable	Min	Max	Mean	StdDev
EMA	99.70	100.49	100.07	0.09
MACD	-0.44	0.58	0.06	0.13
Stochastic	34.96	99.48	79.48	11.19

3.2 Selection of Outputs

The neural networks built in this study were designed to produce an output signal, whose strength was proportional to expected returns over the forward 12-hourly timeframe. In essence, the stronger the signal from the neural network the greater the expectation of a successful trading outcome within the next 12 hours. Signal strength was normalized between 0 and 100.

The target is initially calculated as the maximum percentage price change over the next 12 hours, computed for every element (i) in the input series as:

$$(\text{Highest}(\text{close}_{(i+12)}\ldots\text{Close}_{(i)})-\text{Close}_{(i)}) * 100 / \text{Close}_{(i)} \quad (4)$$

This allows the neural network to focus on the relationship between the input technical variables, and the expected forward price change. When the value of the forward price change is positive, the neural network target is set to 100, otherwise it is set to 0.

3.3 Architecture Choices

In accordance with the design methodology of Vanstone & Finnie (Vanstone and Finnie, 2009), a number of hidden node architectures need to be created, and each one is benchmarked against the in-sample data.

The initial ANN is created and benchmarked with SQRT(n) hidden nodes, where n is the number of input variables. The number of hidden nodes is then increased by one for each new architecture 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 hour method. This method assumes unlimited capital, takes every trade signalled, and measures how much average profit is added by each trade over its lifetime.

4 RESULTS

In the in-sample data, there were 2809 rows selected for training (one row for each occurrence of the price closing above the previous 8 hour highs). Table 2 benchmarks the basic trading characteristics of these rows. These figures are for trading 5 standard contracts ($100,000 euro), and include typical transaction costs (2011).

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 higher forecast positions as and when they occur. As the ANN forecast is allowed to range between 0 and 100, a value of 50 is chosen. This choice is strictly arbitrary, and represents an attempt to match the quality of the trading signals generated to an individual's unique risk appetite. Whilst a more 'scientific' method could be used to determine the optimum threshold, it is unlikely that the one fixed value threshold would be 'best' for different traders. As traders are individuals working under tightly managed risk conditions, it seems important to allow the flexibility to balance the risk within the signal generating process to the specific risk a trader wishes to adopt. This is not a decision which can be taken in isolation from the rest of the trading activities in which the individual is involved.

Table 2: In-sample benchmarks.

Strategy	Profit per hour	Win %	Avg. Profit per Trade	Hours trade open
Simple Breakout	$5.87	39.98%	$137.83	23.41
ANN – 2 hidden nodes	$22.39	52.44 %	$269.24	12.03
ANN – 3 hidden nodes	$20.82	53.03 %	$189.68	9.11

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 to those which it already displays in-sample.

From the above table, it is clear that ANN – 2 hidden nodes should be selected, as it extracts the highest amount of profit per hour. 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.

The 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 3 shows the effect of testing on the out-of-sample data, and includes the effects of the global financial crisis. As such, these out-of-sample figures provide an unusual opportunity to see how this neural network trading system behaved out-of-sample under extremely challenging conditions.

Table 3: Out-of-sample benchmarks.

Strategy	**Profit per hour**	**Win %**	**Avg. Profit per Trade**	**Hours trade open**
Simple Breakout	$5.33	39.11 %	$113.81	21.37
ANN – 2 hidden nodes	$ 21.77	51.72 %	$226.09	10.39

Figures 1 and 2 both show the same trading timeframe. Figure 1 shows the trades the initial strategy took, whilst figure 2 shows the ANN enhanced strategy avoiding these trades due to the signal threshold being below 50.

Figure 1: Example trades from initial system.

Figure 2: ANN enhanced system avoids these losing trades.

5 CONCLUSIONS

The ANN based trading system has performed remarkably robustly, as the out-of-sample performance is remarkably close to the in-sample performance, leading to the conclusion that the ANN is not curve-fit, and should continue to perform well into the future.

Unfortunately, there are no well accepted models of exchange rate determination over shorter term horizons, so it is not feasible to compare the result to other commonly accepted shorter term trading models, as there are none. In many ways, this lack of viable, accepted shorter term models is an indication of the difficulty of shorter term trading.

6 FUTURE WORK

This paper has demonstrated the process of creating a neural network to support a high-frequency foreign currency trading system. As it currently stands, this trading system only signals when to take long positions. Trading short is also quite common in the FX markets, as it allows traders to trade against a currency when they wish. Future work for this system is to develop a neural network to support short side breakout trading.

The choice of the length of the breakout parameter is fixed (and arbitrary). It is expected that a parameter that is dynamic would be of further benefit, and this is also further work for this style of trading.

Further, the variables used as inputs to the neural network are by no means comprehensive within the domain of technical analysis, and a more detailed review of likely variables of influence needs to be conducted within the chosen instruments and timeframes.

Finally, there are a number of other instruments, particularly other highly liquid currencies and index futures, which appear to lend themselves to this style of short-term trading. Further work would be to extend this work across these other securities.

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