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Viktor Manahov
University of Newcastle

Robert Hudson
University of Hull

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Contact: Viktor Manahov - v.manahov@newcastle.ac.uk, Robert Hudson - robert.hudson@hull.ac.uk.
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Viktor Manahov
Dr

Robert Hudson
Prof

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We developed profitable foreign exchange forecasts by applying a special adaptive form of the Strongly Typed Genetic Programming (STGP)-based learning algorithm to five-minute high frequency data of six of the most traded currency pairs. We examined the out-of-sample performance of these intraday technical trading models based on STGP and optimised linear forecasting. We found evidence of economically and statistically significant out-of-sample excess returns, after taking into account appropriate transaction costs.

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1. Introduction

Technological improvements and the spread of computer power enhanced the development of nonlinear forecasting techniques and their applicability in the foreign exchange (FX, hereafter) market. Technical trading tools are based on the assumption that historical data exhibit regularities. Most academic studies in FX literature measured profitability from trades based on daily data execution. However this does not correspond to real-life technical trading strategies used by FX traders. In reality, nearly all technical analysts in the FX are intraday traders who operate at high frequency. Thus, the use of five-minute high frequency data adds realism when analysing trading rules in our experiment. We adopted a more realistic and practical approach by performing technical trading using five-minute high frequency data to generate excess returns after taking into account transaction costs. High frequency trading (HFT) has received little attention in the academic literature to date due its recent emergence. However, this type of trading has recently drawn massive public attention caused by the 'flash crash' in the USA on the 6^{th} of May 2010 and the remarkable increase in HFT volumes. In this paper, we compare STGP forecasting performance with linear forecasting models, which provide good benchmarks against which to compare the predictive ability of the computational models.

2. Background

Saraiya and Mittal (2009) reported that the annual aggregate profits of HFT are $21 billion. Aldridge (2009) applied an omniscient methodology to the FX trading and reported returns of 0.04-0.06% at short trading intervals. Kearns *et al.* (2010) implemented similar high frequency methodology to produce modest profitability without taking into account transaction costs. Bowen *et al.* (2010) used high frequency pairs of FSTE 100 constituent stocks for the period January to December 2007 to generate excess returns both sensitive to transaction costs and speed of execution. While Brogaard (2010) demonstrated that high frequency traders earn significant risk-adjusted returns and Menkveld *et al.* (2011) argued that HFT improves liquidity and the informativeness of quotes. Hasbrouck and Saar (2011) used high frequency data to develop a methodology to identify runs of trades.

In this paper we follow Neely and Weller (2003), who applied the Genetic Programming (GP) technique to half-hourly data of USD/DEM, USD/JPY, USD/GBP and USD/CHF during 1996 in order to find profitable trading rules and investigates market efficiency. The authors failed to report profitability after taking into account transaction costs. For more realistic forecasting purposes, we have implemented an innovative evolutionary STGP technique with no over-fitting of the FX historical data and the additional important factors:

1. We have included more currency pairs and higher frequency data in our experiment. We also performed our experimental tests under different computational techniques. In STGP, the process of estimating the agent's fitness does not include any re-execution of their trading rules based on historical data (over-fitting). This is due to the fact that the artificial traders have already executed their trading rules on the same historical data set and the software (Altreva Adaptive Modeler) is looking only at the realistic returns that they have already made, rather than any hypothetical returns that agents could have made if they were sent back in time again (Witkam, 2012). Therefore, we avoided over-fitting of the data which seems to be one of the biggest forecasting pitfalls.

2. We used a greater number of artificial agents. While Neely and Weller's experiment consisted of 1,000 trading rules, we developed models with 10,000 traders and 10,000 trading rules. A larger population means increased model stability and reduced sensitivity to random factors.

In our experiment we include five-minute high frequency FX data of the most traded pairs of currencies: EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF and USD/CAD. The in-sample trading period in our experiment started on 28th of August 2012 at 7.15pm (GMT) and finished on 8th of February 2013 at 9.50pm (GMT) and consisted of 32,251 real data quotes. The out-of-sample trading began on 8th of February 2013 at 9.55pm (GMT) and finished on 8th of March 2013 at 9.55 pm (GMT) and consisted of 5,948 real data quotes. The study period was chosen on the basis of maximum data availability downloaded from Bloomberg. Similar to real-life FX market, this experiment allowed 24 hours of trading except weekends-trading from 8.15pm (GMT) on Sunday until 10pm (GMT) on Friday.

3. The Linear Forecasting Model

Similar to Neely and Weller (2003), we estimated an autoregressive model for each of the six exchange rates in-sample, as well as out-of-sample, by using only own lagged parameters of the log exchange rate. The maximum lag restriction is 10 lags. Each predictive model is combined with a filter in order to generate a trading rule. We implemented a filter in our experiment to reduce the frequency of trading and the associated transaction costs for periods with small change in the forecasted exchange rate. The actual trading signals are captured in the following order:

If $z_{t-1} = +1$, $\quad z_t = -1$, if $E_t\left(\ln\left(S_{t+1}\right)\right) < \ln S_t - f$,

$$z_t = +1, \text{ if } E_t\left(\ln\left(S_{t+1}\right)\right) \geq \ln S_t - f . \tag{1}$$

If $z_{t-1} = -1$, $\quad z_t = +1$, if $E_t\left(\ln\left(S_{t+1}\right)\right) > \ln S_t + f$,

$$z_t = -1, \text{ if } E_t\left(\ln\left(S_{t+1}\right)\right) \leq \ln S_t + f .$$

Where $E_t\left(\ln\left(S_{t+1}\right)\right)$ is the one-period-ahead forecast of the log exchange rate at time t and f is the filter. The first two lines of equation 1 postulates that if the trading rule possesses a long position at $t-1$, it will change to a short position at t if the forecast indicates a fall by more than the size of f from t to $t+1$ in the exchange rate. The trading rule will maintain a long position if the predicted change in the exchange rate is bigger or alternatively equal to the negative size of f .

4. Experimental Design

4.1. Developing initial trading rules

Table 1.0 represents the main settings of the STGP-based artificial stock market model. Every artificial trader in our experiment has only one trading rule and the genomes of the STGP are the actual trading rules of agents. The initial generation of trading rules is created randomly. Typical GP techniques-such as the crossover recombination technique (randomly chosen parts of two trading rules are exchanged in order to create two new trading rules) and mutation operation (that randomly changes a small part of the trading rule)- are implemented to create later generations.

Hence, trading rules will improve by a natural selection process, because the survival-of-the-fittest principle is in place. The whole process of creating new trading rules is repeatedly performed until at least one trading rule in the population achieves the satisfactory fitness level measured by the fitness function of an agent's investment return over a specified period (Witkam, 2012).

Table 1.0

Artificial Stock Market Parameter Settings

Artificial stock market parameters	
Total population size (agents)	10,0000
Initial wealth(equal for all agents)	100,000
One way transaction costs	2.5 basis points
Significant Forecasting range	0% to 10%
Number of decimal places to round quotes on importing	2
Minimum price increment for prices generated by model	0.01
Minimum position unit	20%
Maximum genome size	4096*
Maximum genome depth	20**
Minimum initial genome depth	2
Maximum initial genome depth	5
Breeding cycle frequency (bars)	1
Minimum breeding age (bars)	80
Initial selection type	random
Parent selection (percentage of initial selection that will breed)	5%
Mutation probability (per offspring)	10%
Total number of quotes processed for each of the six pairs	41,199 (35,251 in-sample and 5,948 out-of-sample)
Seed generation from clock	Yes
Creation of unique genomes	Yes
Offspring will replace the worst performing agents of the initial selection	Yes

*Maximum genome size measure the total number of nodes in an agent's trading rule. A node is a gene in the genome such as a function or a value.

**Maximum genome depth measures the highest number of hierarchical levels that occurs in an agent's genome (trading rule). The depth of a trading rule can be an indicator of its complexity.

4.2. Artificial stock market structure

Our stock market is populated by 10,000 boundedly rational artificial traders. All of the traders are characterised by adaptive learning behaviour represented by the STGP algorithm. The artificial traders are enabled to develop different forecasting rules during different time periods. Hence, the agents in the model are not orientated towards predetermined formation of strategies and, therefore, are free to develop and continually evolve new trading rules.

Artificial traders in the stock market generate wealth by investing in six different currency pairs and the risk free asset represented by cash. Because the models constantly evolve, the traders with well performing trading rules will become wealthier, leading to an enhanced forecasting accuracy of the model. In each period, an artificial trader is keeping his wealth by:

$$W_{i,t} = M_{i,t} + P_t h_{i,t} \tag{2}$$

Where $W_{i,t}$ is the wealth accumulated by trader i in period t; $M_{i,t}$ and $h_{i,t}$ represents the money and the amount of currency pairs held by artificial trader i respectively, in period t ,and P_t is the price of the currency pair in period t .

5. Methods of Analysis

In order to empirically examine the accuracy and most importantly the profitability of the forecasting rules we implemented an *ex-ante* (out-of-sample) testing procedure. An out-of-sample comparison is good practice because we do not know the future performance of the market. If one was to use our strategy in real FX trading it will be based on live data as it evolves, not on the in-sample historical dataset. Also, out-of-sample testing is needed in order to control for the possibility of over-fitting issues. If the in-sample parameters are over-fitted, then it is unlikely that they will perform well in the out-of-sample period. Since most forecasting models represent approximations of the true data generating process, in most cases the availability of a good in-sample fitted model implies neither a necessary nor a sufficient condition for accurate and reliable stock market forecasts (Marcucci, 2005).

6.Empirical results

Tables 2.0 and 3.0 contain in-sample and out-of-sample summary statistics for the distributions of five-minute log exchange rates of the six currency pairs. The distributions show some signs of skewness, but the level of kurtosis is below the excess limit (apart from out-of-sample USD/JPY with reported excess kurtosis of 4.25). Similar to the findings of Hudson (2010), the serial correlations are generally small.

Table 2.0

Sample Statistics

Pair	Mean	Std.dev	Skew	Kurt	ρ(1)	ρ(2)	ρ(3)	Min	Max
EUR/USD	0.00369	0.02530	0.24373	2.80595	0.07432	0.05520	0.04961	1.24690	1.37060
USD/JPY	0.23409	4.62241	0.83322	2.43541	0.19781	0.18207	0.16118	77.4000	94.0300
GBP/USD	0.00457	0.01490	-0.4430	2.47987	-0.0571	-0.0419	-0.7528	1.56330	1.63600
AUD/USD	0.00295	0.00941	-0.3060	2.61107	0.03110	-0.0729	-0.2452	1.01520	1.06150
USD/CHF	0.00264	0.01237	0.20448	2.74220	0.10051	0.09918	0.08511	0.90250	0.96330
USD/CAD	0.00284	0.00834	-0.2167	2.51060	-0.0482	0.01190	-0.0235	0.96360	1.01000

Note: The table include statistics for log foreign exchange rate changes based on in-sample data set, consisting of 35,251 five-minute observations taken 24 hours a day. Mean is multiplied by 100. ρ(*i*) represents the autocorrelation coefficient at lag *i*. Min and Max values measure the smallest and the largest five-minute percentage changes over the in-sample period.

Table 3.0

Sample Statistics

Pair	Mean	Std.dev	Skew	Kurt	ρ(1)	ρ(2)	ρ(3)	Min	Max
EUR/USD	0.02219	0.01584	0.10433	1.47609	0.08101	0.06248	0.04197	1.29660	1.35170
USD/JPY	1.57058	0.84090	0.42302	4.25168	0.19917	0.19851	0.17170	91.1700	96.4000
GBP/USD	0.02575	0.02301	0.48845	2.00760	0.08271	0.06278	0.04299	1.49120	1.58090
AUD/USD	0.01727	0.00526	-0.2680	2.68793	-0.0515	-0.0614	-0.0337	1.01180	1.03720
USD/CHF	0.01563	0.00970	0.38295	2.00029	0.06569	0.04192	0.03127	0.91530	0.95440
USD/CAD	0.01724	0.01057	-0.3574	1.58365	-0.0109	-0.0926	-0.0872	1.00000	1.03420

Note: The table include statistics for log foreign exchange rate changes based on out-of-sample data set, consisting of 5,948 five-minute observations taken 24 hours a day. Mean is multiplied by 100. ρ(*i*) represents the autocorrelation coefficient at lag *i*. Min and Max values measure the smallest and the largest five-minute percentage changes over the out-of-sample period.

We measure profitability by two primary criteria: 1) the number of correct hits (forecasts) and 2) the generated excess return from trading the three financial instruments. By implementing the hit ratio, we test the percentage of time that the model has good sign of predictability, which is quantified by:

$$\text{Hit ratio (\%)} = \frac{\text{Number of correct forecasts}}{\text{Number of generated long / short orders}} \times 100 \qquad (3)$$

The excess return represents the amount received from trading in excess of the risk free rate. It is the continuously compounded return on each of the currency pairs price, minus the value of the daily continuously compounded rate converted from the annualised investment yield on a three month US Treasury bill:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) - r_{t-1} \qquad (4)$$

Where P_t is the price of each of the six currency pairs traded at period t, and r_t is the risk free rate set at the value of daily continuously compounded rate converted from the annualised investment yield on a three month US Treasury bill (data up to 8th of March 2013 was downloaded from the Federal Reserve statistical release website at www.federalreserve.gov/releases/h15).We trade each of the six currencies against the US dollar and this is the reason why we adopted the US risk free T bill rate, instead of employing other risk free instruments in deriving the excess returns. On the other hand, the reason for forecasting the excess return is because it provides a measure of how well our models perform relative to the minimum returns gained from depositing the money in a risk free manner. We then compared the out-of-sample forecasting performance of the autoregressive forecasting model and the STGP model. Tables 4.0 and 5.0 clearly demonstrate the superiority of the STGP technique. A hit ratio above 50% is a sign of actual profitability from trading.

Table 4.0

Ex-ante comparison of the predictive strength and profitability of the autoregressive forecasting model.

Pair	EUR/USD	USD/JPY	GBP/USD	AUD/USD	USD/CHF	USD/CAD
Number of long/short orders	674	603	599	621	584	611
Number of correct hits	340	303	304	318	298	313
Successful hit ratio	50.4%*	50.2%*	50.7%*	51.2%*	51.0%*	51.2%*
Excess return	1.21%	1.01%	1.46%	1.90%	1.81%	1.95%

[a] The table reports the number of times the autoregressive out-of-sample forecasting model correctly predicts the direction of the six currency pairs and profitability of 5,948 observations for each pair. A ratio market with asterisk (*) indicates a 95% significance based on a one-sided test of H_0:p=0.50 against H_a:p>0.50. . [b]The risk-free rate is set at the value of daily continuously compounded rate converted from the annualized investment yield on a 3-month US Treasury bill (up to 08/03/2013).

Table 5.0

Ex-ante comparison of the predictive strength and profitability of the STGP forecasting model.

Pair	EUR/USD	USD/JPY	GBP/USD	AUD/USD	USD/CHF	USD/CAD
Number of long/short orders	727	692	688	709	698	691
Number of correct hits	393	372	376	391	382	386
Successful hit ratio	54.0%*	53.7%*	54.6%*	55.1%*	54.7%*	55.9%*
Excess return	3.99%	3.76%	4.62%	5.44%	4.81%	5.93%

[a] The table reports the number of times the STGP out-of-sample forecasting model correctly predicts the direction of the six currency pairs and profitability of 5,948 observations for each pair. A ratio market with asterisk (*) indicates a 95% significance based on a one-sided test of H_0:p=0.50 against H_a:p>0.50. . [b]The risk-free rate is set at the value of daily continuously compounded rate converted from the annualized investment yield on a 3-month US Treasury bill (up to 08/03/2013).

The STGP technique reports higher hit ratios and excess returns than the autoregressive predictive model. The STGP for USD/CAD recorded the highest hit ratio of 55.9% followed by the AUD/USD pair with 55.1% and USD/CHF with 54.7%, then GBP/USD with 54.6%, and EUR/USD with hit ratio of 54.0%. USD/JPY pair recorded the lowest STGP hit ratio of 53.7%. This is reflected in the actual profitability from trading. FX transaction costs dramatically declined to 2 basis points in the last few years (from about 10 basis points in the 1970s). Neely and Weller (2003) investigated the effect of up to two basis points of intraday technical trading transaction costs for one-way transactions. We assigned slightly higher transaction costs of 2.5 basis points for one-way high frequency technical trading. We implemented slightly higher transaction costs in order to guard against data over-fitting, which seems intuitively reasonable. While the USD/CAD currency pair generated the highest *ex-ante* excess return of 5.93%, the EUR/USD pair reported an excess return of 3.99%.

Moreover, we conducted a one-sided test to investigate whether the hit ratios are significantly different from the benchmark of 0.5 (a 95% significance level). Under the null hypothesis the test has no predictive effectiveness power $(H_0 : p = 0.50$ against $H_0 : p > 0.50)$. The statistical tests rejected the null indicating that the hit ratios of the three indices are significantly different from 0.50. This important finding confirms the ability of our forecasting models in the prediction of the six currency pairs.

7. Concluding Remarks

In this paper, we developed realistic trading scenario and investigated the predictability and profitability of the six most traded currency pairs. We are not aware of any other study which implements the STGP technique to generate *ex-ante* excess returns by using five-minute high frequency data and taking into account appropriate transaction costs. We found that the STGP technique is superior to traditional econometric forecasting models such as optimised linear forecasting.

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