

Evolutionary Money Management

Philip Saks*

Dietmar Maringer†

*Centre for Computational Finance and Economic Agents, University of Essex

†Economics and Business Faculty, University of Basel

Abstract

This paper evolves trading strategies using genetic programming on high-frequency tick data of the USD/EUR exchange rate covering the calendar year 2006. This paper proposes a novel quad tree structure for trading system design where the functions of the trees are related to initiating (“entry”) and terminating (“exit”) long and short positions. Thus, evaluation is contingent on the current market position. Using this architecture the paper investigates the effects of money management. Money management refers to certain measures that traders use to control risk and take profits, but it is found that it has a detrimental effects on performance.

1 Introduction

The foreign exchange (FX) market is the largest financial market in the world. In theory, exchange rates should be intimately linked to macro economic variables, such as interest rates, inflation, money supply and real income. However, in their seminal paper, Meese and Rogoff [10] found that these fundamentals are useless in forecasting exchange rate changes even at medium frequencies. This is known as the *determination puzzle of foreign exchange*. At shorter time horizons many traders tend to use *technical analysis* in decision making [1]. Technical analysis attempts to forecast future price changes based on historical observations. This broad definition covers a wide range of methods from visual pattern recognition to moving averages and more elaborate schemes. Traditionally, it has encountered much skepticism from academia since it clearly contradicts the *Efficient Market Hypothesis* (EMH) – one of the cornerstones of modern finance [5].

During the past few decades, there has been an increasing interest in technical analysis among financial economists and extensive literature has emerged on the subject. There is a general consensus that technical analysis on a daily frequency has been profitable in the past [3, 9, 8]. In contrast, this paper uses high-frequency intraday tick data and considers both a frictionless environment and trading under market frictions through the quoted bid-ask spread. Instead of using predetermined rules, the system evolves its own trading strategies using *genetic programming* (GP). GP has previously been applied to trading rule induction for foreign exchange markets, but the results are mixed. In the early nineties GP was found to produce significant profits [6, 2], but performance has since deteriorated [4, 11].

The standard approach of GP in trading rule induction is to use a single tree structure that makes buy or sell recommendations. This paper proposes a novel multiple tree structure consisting of four (quad) trees for ternary decision problems. Hence, strategies can take short, neutral and long positions. Which tree is evaluated is contingent on the current market position. In addition, the benefits of money management are examined. Money management refers to certain measures that traders use to control risk and take profits, implying that closing of positions can be initiated by events other than “standard” buy/sell signals. To reflect this in an automated trading system, different rule sets, contingent on the current position, are used. Hence, a negative entry signal is not necessarily seen as an exit signal, but entirely different rules are evaluated to find exit signals. Furthermore, these exit signals can be based on other indicators or information.

The paper is outlined as follows. Section 2 describes the fitness function, model and experimental settings. This is followed by empirical results in Section 3. Finally, Section 4 concludes and gives pointers to possible future research.

2 Framework

2.1 Objectives and Fitness Function

The choice of objective function is essential in evolutionary computation. Since this paper is concerned with trading system design and ultimately generation of wealth, it is natural to seek inspiration in *economic utility theory*. Cognitive psychology has revealed that, in evaluating different outcomes, reference dependence plays a crucial role [7], and so does the frequency of wealth evaluation [15]. To capture this, the period over which the trading rule is optimized is divided into I sub-intervals and a utility is evaluated for each interval. Let the return within an interval i be defined as, $r_i = \frac{w_t - w_{t-k}}{w_{t-k}}$ where k is the length of the interval. A modified terminal interval wealth is then introduced, $\hat{v}_i = v_0 \cdot (1 + r_i)^{\lambda \mathcal{L}_i}$ where $\mathcal{L}_i$ is a Boolean variable indicating a loss and $\lambda > 1$ implies loss aversion, i.e., a greater sensitivity to decreases in wealth, while $\lambda = 1$ models no additional disutility of losses beyond risk aversion. In this paper a unit investor is considered such that $v_0 = 1$. Assuming a power utility function, the value of an interval is, $U(\hat{v}_i) = \frac{\hat{v}_i^{1-\gamma}}{1-\gamma} - \frac{1}{1-\gamma}$ if $\gamma > 1$ (risk aversion) and $U(\hat{v}_i) = \ln(\hat{v}_i)$ if $\gamma = 1$ (risk neutrality). From this the objective function simply follows as the average interval utility, $F = \frac{1}{I} \sum_{i=1}^I U(\hat{v}_i)$.

2.2 Model

The purpose of this paper is to evolve trading models using genetic programming. The traditional approach in the context of FX forecasting is to evolve ternary decision rules where outputs correspond to long, neutral or short positions in a given currency (here: USD).

In the context of binary trading models it has previously been found that using a dual tree structure instead of the traditional single tree model has significant impact on performance, especially when market frictions are taken into account. [14]. Capitalizing on these findings this paper proposes a unique quad tree structure. The four trees consist of a long entry (T1), long exit (T2), short entry (T3) and short exit (T4).

Each tree returns a Boolean variable, but which tree is evaluated depends on the current market position. Some cases deserve further explanation. E.g., when T1 and T3 are both true, the signal is ambiguous and a neutral position is maintained. Moreover, when both entry and exit signals are true, the strongest views are given precedence such that directional views trump neutrality.

One objective of this paper is to examine the effects of money management on trading strategies. This is done by comparing strategies with special grammars for the exit strategies (T2 and T4), to strategies where the grammar is the same across all the trees. The function set for the entry strategies (T1 and T3) consists of numeric comparators, Boolean operators and addition. The terminals include the variables price and moving averages thereof (`price`) and the time of day (`time`), and special constants are available for conditioning on time (`timeConst`), and the difference between price indicators (`pConst`).

In practice, traders employ various exit strategies for money management, such as stop losses and profit targets. To capture these ideas the exit strategy grammar consists of the entry grammar plus information about the current profit, drawdown and duration of a trade.

2.3 Parameter Settings

In the following computational experiments a population of 500 individuals is initialized using the *ramped half-and-half* method. It evolves for a maximum of 50 generations, but is stopped after 20 generations if no new elitist (*best-so-far*) individual has been found. Each of the trees in the programs are constrained to a maximum complexity of 25 nodes.

As fitness functions, three different utility functions are considered: risk neutral ($\gamma = 1$, $\lambda = 1$), risk averse ($\gamma = 35$, $\lambda = 1$) and loss averse ($\gamma = 35$, $\lambda = 1.15$). Each Block is divided into a number of sub-intervals, each consisting of $I = 1000$ samples.

2.4 Data

The data is provided by OANDA FXticks, and comprises of tick data on the USD/EUR exchange rate covering the calendar year 2006. This constitutes a total of 3 894 525 bid-ask observations, and on average

there are more than 12 000 per trading day. The exchange rate is sampled every 10 ticks, which yields 389 452 samples. On average this is close to 1 minute sampling in calendar time. The data comprises bid-ask quotes, but in the following the statistical properties of the logarithmic middle prices are analyzed. The USD/EUR series exhibit strong intraday effects, e.g., the trading activity is higher during European business hours. Moreover, there are two distinct peaks around 08:00 and 14:00 GMT with high activity, separated by lower activity at noon. The entire data set is split into four equal-size blocks of 97,364 samples each. Henceforth the blocks are denoted; I, II, III and IV.

3 Empirical Results

In this section the results from rolling window estimation and testing on blocks I to IV are presented. For statistical inferences ten independent runs are considered for both the entry-entry and entry-exit grammar strategies. Moreover, strategies are evolved both under the assumption of frictionless trading and in the presence of market frictions, i.e., trading occurs on middle prices or through the bid-ask spread, respectively.

The median in-sample fitness value is 60.44 for Block I, and out-of-sample it decreases to 39.05 on Block II. However, when Block II is used for training, the median fitness is identical, which indicates that the strategies have captured the underlying dynamics of the price process perfectly. For the remainder of the blocks the performance is comparable. Overall the interval returns appear relatively normal, albeit with some excess kurtosis in some of the blocks. Under frictionless trading the evolved strategies simply capture the mean-reversion effect inherent in the data as documented in Section 2.4. Exploiting this microstructural effect is a winning strategy regardless of the utility functions considered in this paper. This is true for both the entry-entry and entry-exit grammar strategies. The strategies are generally neutral less than 6% of the time, and the proportion of winning trades is approximately 70%. Given the high turnover it is not surprising that the average return of trades are tiny (≤ 0.1 bp).

Naturally, the introduction of market frictions has an adverse effect on performance. Under risk neutrality the in-sample median fitness in Block I drops to 7.78 and 8.08 for the entry-entry and entry-exit grammar strategies, respectively. What is more interesting is that the out-of-sample median fitnesses in Block II are positive for both grammars (4.51 and 4.37). Unfortunately, this pattern does not repeat itself during the later periods. This holds for all utility functions. It becomes more difficult to find trading opportunities and the strategies remain neutral a greater proportion of time. Under loss aversion the strategies are neutral 70% of the time.

To test the null hypothesis that the evolved strategies have uncovered significant regularities, their fitness values are compared to that of 1000 randomly initialized strategies. The vast majority of strategies outperform the random strategies at the 0.05 level of significance. For the sake of brevity, detailed results are given elsewhere [13].

As mentioned previously, a main objective of this paper is to examine the effects of money management for different types of speculators. To test formally whether money management, i.e., an extended exit grammar, makes a difference, the Wilcoxon rank sum test is employed for each block and for each utility function. Only Block IV out-of-sample under risk neutrality is significant at the usual level. In the context of the other results, this can clearly be treated as a spurious rejection and does not lead to an overall rejection of the null hypothesis. It must therefore be concluded that money management has a detrimental effect on utility, since the evolved strategies do not make use of it. Osler [12] offer a possible explanation for this result: in the foreign exchange markets, stop and limit orders tend to be clustered around round numbers giving rise to distinct support and resistance levels, where trend reversals are more likely to occur. This has not been taken into account in this paper.

4 Conclusion

This paper evolves trading strategies using genetic programming (GP) on high-frequency tick FX data. Furthermore, it proposes a novel quad tree structure for trading system design to allow for a money management system where exit rules can be based on additional indicators and triggers than rules for entering positions.

This paper makes a distinction between entry and exit strategies, thus providing a more accurate description of the “money management” problem faced by real traders. In an environment without transaction costs the strategies exploit the significant mean reverting properties of the returns series. Under transaction costs and loss aversion, however, the strategies spend considerably more time in a neutral position since there are fewer satisfying opportunities. The downside is that generalization can suffer as a result. However, if the patterns discovered in-sample have poor quality, then loss aversion is beneficial because it promotes cautious trading that limits transaction costs. The results also suggest that money management has a detrimental effect on utility, and raises the question as to why it is extensively used by practitioners, which could be investigated in future research.

References

- [1] Allen, H. and Taylor, M. P. [1990], ‘Charts, noise and fundamentals in the London foreign exchange market’, *The Economic Journal* **100**(400), 49–59.
- [2] Bhattacharyya, S., Pictet, O. V. and Zumbach, G. [2002], ‘Knowledge-intensive genetic discovery in foreign exchange markets’, *IEEE Transactions on Evolutionary Computation* **6**(2), 169–181.
- [3] Chang, K. and Osler, C. L. [1999], ‘Methodical madness: Technical analysis and the irrationality of exchange-rate forecasts’, *The Economic Journal* **109**, 636–661.
- [4] Dempster, M. A. H. and Jones, C. M. [2001], ‘A real-time adaptive trading system using genetic programming’, *Quantitative Finance* **1**, 397–413.
- [5] Fama, E. F. [1970], ‘Efficient capital markets: A review of theory and empirical work’, *Journal of Finance* **25**(2), 383–417.
- [6] Jonsson, H., Madjidi, P. and Nordahl, M. G. [1997], Evolution of trading rules for the FX market or how to make money out of GP, Technical report, Institute of Theoretical Physics, Chalmers University of Technology.
- [7] Kahneman, D. and Tversky, A. [1979], ‘Prospect theory: An analysis of decision under risk’, *Econometrica* **47**(2), 263–291.
- [8] LeBaron, B. [2002], Technical trading profitability in foreign exchange markets in the 1990’s, Technical report, Brandeis University.
- [9] Maillet, B. and Michel, T. [2000], ‘Further insights on the puzzle of technical analysis profitability’, *The European Journal of Finance* **6**, 196–224.
- [10] Meese, R. and Rogoff, K. [1983], ‘Empirical exchange rate models of the seventies, do they fit out-of-sample?’, *Journal of International Economics* **14**, 3–24.
- [11] Neely, C. J. and Weller, P. A. [1999], Intraday technical trading in the foreign exchange market, Technical report, Federal Reserve Bank of St Louis.
- [12] Osler, C. L. [2003], ‘Currency orders and exchange rate dynamics: An explanation for the predictive success of technical analysis’, *The Journal of Finance* **58**(5), 1791–1819.
- [13] Saks, P. and Maringer, D. [2008a], Evolutionary money management, Technical report, Centre for Computational Finance and Economic Agents, University of Essex.
- [14] Saks, P. and Maringer, D. [2008b], Genetic programming in statistical arbitrage, in M. Giacobini, ed., ‘EvoWorkshops 2008’, Springer, pp. 73–82.
- [15] Thaler, R., Tversky, A., Kahneman, D. and Schwartz, A. [1997], ‘The effect of myopia and loss aversion on risk taking: An experimental test’, *The Quarterly Journal of Economics* **112**(2), 647–661.