Algorithmic Trading in Foreign Exchange Based on Order Flow

Mat-2.4108 Independent Research Projects in Applied Mathematics

6th February 2009

Helsinki University of Technology
Department of Engineering Physics and Mathematics

Tuomas Nummelin

62832W
1. Executive Summary
The goal of this study was to construct a simplified simulation model for foreign exchange and to test the performance of trading algorithms. Some of the tested algorithms use the information from order flow and the goal was to see whether significant insight is gained from this. After rigorous analysis it could be deemed that the utilisation of order flow information does benefit the algorithms. However, the results depend on how the information is used. Differences in performance are evident. The performances of algorithms vary from a mediocre and stable performance lacking the exceptional high profits, to a performance altering much from the top profits to the largest loses. It is also noteworthy that the different algorithms performed well, with both a simulation data set and with a real daily data set. This information encourages us to seek better ways to utilize the order flow data.

2. Motivation and Background for Research
The focus of this study is on automated trading in foreign exchange (forex, FX). Focusing on a microstructure-based order flow we hope to enhance automated trading in FX markets. In order to adapt the microstructure view to automated trading, we first look at the FX market and the FX spot rate determination models, examining microstructure based models, and determine whether they can be used in automated trading or not. This is the first part of this study while the quantitative analysis of the chosen model implementation is the second one.

The foreign exchange market is a cash inter-bank or inter-dealer market, which is the biggest and most liquid market in the world. The average daily turnover in traditional FX markets has grown by 69% since April 2004, to $3.2 trillion in April 2007 (BIS, Triennial Central Bank Survey 2007). However the recent crisis in financial markets has an effect in FX market as well, but it is still too early to say what are the lasting consequences for market. Although the potential markets and technical improvements in information and communication technologies (ICT) the FX markets have turned in to actual 24/7 real time electronic markets using electronic trading systems to be very attractive market. The use of automated trading systems has increased (www.wikipedia.com) and it is estimated that around 25% automated trading in 2008 does all trade in FX markets.
3. **Foreign Exchange Market: Brief Overview About Models & Market**

Traditionally, the models for FX spot rate have been extensively based on macro exchange models, which pay little attention to how actual trading in the FX market is carried out, even though macro economic models do take into account such factors as GDP, monetary politics, etc. These models have been used to model medium to long term (a few months to years) developments in FX rates. However, these models have little or no prediction power in the short term (Meese and Rogoff 1983, 1997). The implicit assumption incorporated in macro models is that the details of trading (i.e. who quotes currency prices and how the trade takes place) are unimportant to exchange rate changes over months and quarters or longer. In contrast, micro models examine how information relevant to the spot price of the currency is reflected in the spot exchange rate via trading process. Based on this microstructure, the trading process is not an ancillary market activity that can be ignored when considering exchange rate behaviour. Instead, the trading process can be seen as a crucial factor in the process that determines the FX spot rate.

The FX market consists of two segments; the interbank market and the customer market. The advancements in trading technology have reshaped the structure of the FX market; the electronic brokers in interbank markets and the internet trading for customers have been the main driving factors of the restructuring (Rime). In the interbank market, trading is either direct (bilateral or taking place between dealers) or brokered (interdealer trades). Prior to the Internet revolution, customers traded with the bank. However, nowadays customers have the possibility to trade through electronic brokering systems which have become the de facto systems of today. Therefore, we should consider customers as the ultimate end-users of currency. Customers can be broadly defined as being central banks, governments, importers and exporters of goods, financial institutions, like hedge funds, and private individuals. The market is centralised unlike before the ICT improvements when the FX market was decentralised call market. The fundamental nature of currency trading (i.e. due different time zones there exists a continuous need to recognize the value of different currencies) led to the decentralised and continuous market.

4. **Microstructure Models**

Market microstructure is a part of finance concerning in details how the trading of assets occurs in the markets. The main focus of microstructure models is how the trading process affects asset prices, quotes, transaction costs, volumes and trading behaviour. The earliest microstructure models focused on macro aspect of the markets and considered long term economical scale issues in the markets. However until the 1980-90’s the microstructure models have not been seen as very prominent in short-term exchange rate prediction. One relevant fact is that the ICT technology has made it possible to record detailed data about transactions in the markets and give researchers the needed empirical data to develop models. However, it is still today one drawback of microstructure models that they need to have sufficient data to validation. The development in microstructure models has been fast and profitable.
A major development in microstructure modeling in FX was achieved in 1999, when Evans and Lyons (Evans and Lyons, 1999) presented their paper about order flow and exchange rate dynamics. They introduced a simple model, which captured the high $R^2$ statistics in daily DM/USD and YEN/USD spot rate dynamics. The overall fit of the model is striking, compared to the traditional macro models, with $R^2$ statistics of 64% and 45% for the DM and YEN respectively. It is remarkable that the model captures the essentials from the macro point of view as well as the micro point of view. The model considers that all macro information (i.e. interest rate) is considered public information. Private or non-public information (i.e. order flow) is based mainly on micro indicators. The information process or aggregation of the private information is embedded in the order flow which is the source of information diffusion in the model. Even though the model is better than traditional macro economic models, it still is far from perfect. To some extent, models with roughly 50% $R^2$-statistics can be regarded as good models in the field of FX.

The rationale behind order flow was analysed more closely and developed further by Evans and Lyons in 2004 (Evans and Lyons, 2004). This time they took a different approach to exchange rate predictions; they focused on information sets and the diffusion of these sets in the markets. Their model is based on rational expectations (rational expectations and portfolio shift models can be seen as two of the most used model ideas in microstructure). The sum of present values of the measured macroeconomic fundamentals and fundamentals which are not explained with macroeconomic fundamentals, i.e. microstructure measures, form a relation for the prediction of exchange rate. The key empirical findings of their paper include transaction flows, forecasts of future macro variables, such as output growth, money growth, and inflation. Transaction flows generally forecast these macro variables better than spot rates do. Transaction flows forecast future spot rates, and though flows convey new information about future fundamentals, much of this information is still not captured in the spot rates one quarter later. These findings indicate that order flow has a significant role in exchange rate prediction through several different channels.

A different point of view to market dynamics comes from Bacchetta and Van Wincoop (2004). Their model is based on heterogeneous information of standard dynamic monetary model for exchange rate determination. Their findings support the idea that heterogeneous information and different risk attitude through market makers disconnect changes in exchange rate from macro fundamentals in the short run and the value of the order flow as the distributor of private information.

Danielson and Payne (2002) analyse the forecasting power of order flow in different time horizons and found that the order flow has significant meaning in exchange rate forecasting. They examine different currency pairs and cross-reference their findings with other currency pairs closely related to the original pairs’ order flows.

Evans and Lyons (2005) take a more detailed look at order flows and separate order flows in different segments and find that order flows based on
heterogeneous customers carry more information about the future values of the fundamentals when customers focused on long-term investments.

The central banks have also been keen to understand the FX market microstructure from the regulatory point of view and also in extreme situations, where interventions are needed, to understand the possible impacts (Vitale P, 2006). The research area of the microstructure and order flow based models in FX is a promising research field in the near future. It can be noted that the point of view has expanded slightly towards the Hidden Markov Processes that are seen as a new, very prominent, but loosely microstructure based method to predict exchange rates.

5. Automated Trading with Information from Microstructure Models

In this section we consider, which improvements are possible in automated trading with the help of better understanding of the market microstructure. In chapter 5.1, we define the simulation market model, which is used to model FX market.

5.1 Simulation Model for FX Market

The simulation model is a portfolio shift model, where the source of the variation in exchange rates is based on shifts in portfolio balance of the customers. The model is based on the work of Evans and Lyons (1999). This model was chosen as the basis of the simulation because of its simplicity and the fact that no model has performed consistently better in exchange rate prediction in all time horizons. Since the main point of this study is to develop a trading algorithm, the use of this simplified model for markets seems reasonable. A simulation model based on rational expectations could have been an alternative approach. However, the alternative approach was discarded because it would have led to the use of impractical estimations.

The portfolio shifts are not common knowledge at the time of occurrence. Common knowledge is known to everyone in the markets (e.g. current exchange rate and everyone knows that everyone knows that everyone knows ad infinum). The shifts are large enough that the clearing of the market requires rate adjustments of the spot rate. The fact that a portfolio shift is not common knowledge at the time of occurrence serves as an initiating source of order flow. When a customer places private (not publically observed) quotes to dealers who trade among themselves in the interdealer markets to share the resulting inventory risk. The market learns about the initial portfolio shifts through interdealer trading. Though it can be considered common practice that dealers do not hold overnight risks. The inventory risks are shared with the public. The inventory risk is not defined in detail. It is used as concept in potential loss due the inventory, which adjust the actions of traders. The public’s demand for foreign currency assets has to be less than perfectly elastic because if the currency assets are imperfect substitutes, price adjustments are required to clear the market. Innovations in the model are considered in two parts; public information (standard macro fundamentals) and non-public, private information
in portfolio shifts. However, the model does not take into account the underlying source of these portfolio shifts.

Let us consider a pure exchange economy with $T$ trading periods. The economy has two assets; riskless and risky with stochastic payoff representing the FX. The pay of $T+1$ periods in the FX, denoted $F$, is composed of a series of increments $r_t$, observed before trading in each period. This flow of realised increments represents publicly available macro economic information (e.g. interest rate changes).

$$F \equiv \sum_{t=1}^{T+1} r_t, \quad r_t \sim N(0,\Sigma_t) \quad i.i.d$$

(1)

The simulated FX market is modelled as a decentralised dealership market with $N$ dealers indexed by $i$, and continuum of non-dealer customers indexed by $z$ in interval $[0,1]$. Within each trading period three rounds of trading are done. In the first round, dealers trade with customers (the public), i.e. receive the customer order flow, which carries the information about the portfolio shifts of those customers. In the second round, dealers trade among themselves in interdealer market to share the resulting inventory risk. In the third round, dealers trade again, but this time with the public to share risk more broadly.

![Figure 1. Timing of the period](image)

Next we consider the different rounds of trading.
Round 1

At the beginning of each period t in round 1, all market participants observe \( r_t \), period’s t increment for payoff. Based on \( r_t \) and all other available information (both public and private information) each dealer chooses simultaneously an independent price with which he/she agrees to sell and buy any amount of currency to his/her customers. We denote dealer-price for round 1 for dealer \( i \) as \( P_{i1} \). Dealer-price is a mapping from \( r_t \) and all other information to real numbers. The mapping is defined by dealer preferences. The value of \( P_{i1} \) can be the same among multiple trades but it does not have to be. Every dealer receives net customer orders in the value of \( c_{i1} \) that is executed by each dealer’s quote price \( P_{i1} \). \( c_{i1} < 0 \) denotes net customer sales (dealer purchases). Each net customer order \( c_{i1} \) is independent across dealers. Customer net orders are distributed independently from \( r_{i1} \). Customer order realisations are distributed \( c_{i1} \sim N(0, \Sigma_c) \). These initial customer orders can be seen as preferred bilateral customer transactions. These customer orders represent the portfolio shifts on the part of the non-dealer public information and the realisation of these orders is not publically observed.

Round 2

Round 2 is the interdealer trading round. In the beginning of the round, each dealer independently and simultaneously chooses his/her price with which he/she is willing to buy and sell any amount among the dealers. The interdealer price \( P_{i2} \) for trader \( i \) is a mapping of \( P_{i1} \) and \( c_{i1} \) to real numbers. These interdealer quotes are observable and available to all dealers in the market. Then each dealer independently trades on the other dealers’ quotes. The orders on the same quoting price are equally distributed among the dealers who are quoting that price. Let \( T_{i2} \) denote the (net) interdealer trade initiated by dealer \( i \) in round 2. At the end of round 2, all dealers observe the net interdealer order flow from that period

\[
\Delta x = \sum_{i=1}^{N} T_{i2}
\]

Equation (2) is the interdealer order flow and it is observed without noise, though adding noise to the equation does not affect the estimates. FX market interdealer order flow is recorded, because dealer-dealer trades are observable. However, customer-dealer trades are not publically observed. The signals of the customer order flow are embedded in the interdealer order flow and the signals from the former can be observed to some extent.

Round 3

In round 3 dealers share the inventory risk with the non-dealer public. The simulation model is derived from the Evans and Lyons (1999) model, which
focuses on daily exchange rate prediction. However, much shorter time periods (minutes) are considered in our simulation. In their paper Evans and Lyons (1999) considered round 3 as an overnight risk sharing round. Although in the minute concept round 3 is still a risk sharing round, it is also more speculative. Initially, each dealer simultaneously and independently quotes a price \( P_{i3} \) at which he/she agrees to buy and sell any amount. These quotes are observable and available to the public. The number of customers is large compared to the number of dealers, implying that the public's capability to bear risk is greater than that of dealers'. Therefore dealers set the prices according to the public's willingness to bear the inventory imbalance risk. In the concept of daily trade, there are no overnight net positions for dealers whereas in the minute concept the imbalance risk can be seen as the unbearable exposure to exchange rate variation. Typically this means that each dealer has limited currency positions, which are set to keep risks acceptable. These round 3 prices are conditioned by the round 2 interdealer order flow. The interdealer order flow informs the dealers of the size of the total inventory that the public needs to absorb in order to achieve stock equilibrium. Knowing the size of the total inventory that the public needs to absorb is not sufficient for determining the price for round 3. Dealers need to know the risk-bearing capability of the public (normal assumption is that it is less than infinite). Given negative exponential utility, the public's total demand for risky assets in round 3, denoted by \( c_3 \), is a linear function of its expected return that is conditional on public information:

\[
c_3 = \gamma \left( E[P_{3,t+1} | \Omega_3] - P_{3,t} \right)
\]

Where the positive coefficient \( \gamma \) captures the aggregate risk-bearing capacity of the public, and \( \Omega_3 \) is the public information available at the time of trading in round 3.

**Equilibrium**

The dealer's problem is defined over four choice variables, the three price quotes \( P_{i1} \), \( P_{i2} \), and \( P_{i3} \), and the dealer's interdealer trade \( T_{i2} \) (the latter being a component of \( \Delta x \), the interdealer order flow). The more detailed reasoning of Bayes-Nash Equilibrium in Evans and Lyons (1999) leads to optimal trading strategy having the price difference in period \( t \) and \( t-1 \) as

\[
\Delta p_t = r_t + \lambda \Delta x_t
\]

Where \( \lambda \) is a positive constant. The fact that this price change includes the innovation in payoffs \( r_t \) one-for-one is unsurprising. The \( \lambda \Delta x \) term is the portfolio shift term. The no arbitrage conditions ensure that, within a given round, all dealers quote a common price. Given that all dealers quote a common price, this price is necessarily conditioned on common information only. Even though \( r_t \) is common information in the beginning of round 1, the order flow \( \Delta x_t \) is not observed until the end of round 2. The price for round 3 trading, \( P_{3,t} \), therefore reflects the information in both \( r \) and \( \Delta x \). Interdealer order flow carries the signals from initial portfolio shifts, if it is assumed that the dealers’ trade is based on initial customer order flow and in that sense interdealer order flow communicates the initial portfolio shifts in the market. However, the aggregated
information about portfolio shifts is absorbed into the market and the price is adjusted based on known information about the relation between interdealer order flow and subsequent price adjustments. This process of information flow takes a finite amount of time.

For simulation purposes we define empirical implementation of the price difference equation:

\[ \Delta p_t = \beta_1 \Delta (i_t - i_t^*) + \beta_2 \Delta x_t + \eta_t \]  

where \( \Delta p_t \) is the change in the log spot exchange rate from the end of period \( t-1 \) to the end of period \( t \), \( \Delta (i_t - i_t^*) \) is the change in the overnight interest differential from period \( t-1 \) to period \( t \) (* denotes foreign currency), and \( \Delta x_t \) is the order flow from the end of period \( t-1 \) to the end of period \( t \) (negative sign denotes net sales of the home currency).

The overnight interest rate is the macro fundamental of the model. It is assumed to bring all macro information into the model. In the simulation market the empirical pricing relation is used to adjust exchange rate, accordingly

\[ \Delta p_t = \ln S_t - \ln S_{t-1} \]
\[ S_t = S_{t-1} e^{\Delta p_t} \]  

where \( S_t \) is the spot exchange rate.

In the simulation market, order flow has three components, two of which are based on trading algorithms, and one which is a combined order flow from other dealers in the market. The relative sizes of the order flows can greatly influence the dynamics of the market and this can be seen as one interesting factor in the simulation model. The simulation market model is based on an equilibrium model, where it is assumed that unless shifts occur in the portfolios balance on the market, it tends to stay in equilibrium state. The non-algorithmic dealers’ order flows in period \( i \) are assumed to be normally distributed, because it is assumed that each dealer’s customer order flow is independently normally distributed. This assumption is based on the model assumption of round 2 trading strategies. In round 2, the dealers trade some fraction of customer order flow as their interdealer market flow, which leads to a sum distribution, which can be modeled as a normal distribution \( \text{N}(0,\sigma^2) \). The normal distribution parameters can be seen as average values of the periodic values of the whole market. Hence we simulation market model is based on market orders, if we generalise the concept of limit orders. We can see that the limit orders can be seen as a part of the order flow in a period, just like the market orders in that period. However, the limit orders could give a more detailed view of the buying/selling pressure of the market. In certain cases, when the triggering condition for a limit order is met, the limit order can be executed in the same way as a market order. Limit orders can be considered to buffer the changes in exchange rate.
Figure 2 Overview of simulation model

Figure 2 shows the components of simulation model and some basic relationships between components. In addition customers are added to algorithms. However, those customers are not explicitly modeled in simulation. Algorithms are assumed to take customers in account as algorithms try to maximize their own profit.

5.2 Trading Algorithm Based on Microstructure Knowledge.

In order to analyse microstructure based algorithms in FX market, we test three different kinds of models. Recursive reinforced learning (RRL) based model is not truly dependent on understanding the microstructure of the market. However, to some extent it can be regarded as the algorithm that is based on microstructure ideology. A more detailed description of RRL can be found in Exploring Algorithms for Automated FX Trading – Constructing a Hybrid Model Mat-2.4177 Seminar on Case Studies in Operations Research, Spring 2008. The fundamental idea of the RRL is also used in the second microstructure algorithm, which is for the most part of similar construction to the RRL. In principle, it tries to model the order flow using the RRL to achieve reasonable predictions of exchange rate movements. The third model is a combination of the basic RRL and some directly order flow based indicator (and/or flow itself).

The order flow RRL algorithm is fundamentally similar to the normal RRL algorithm, which uses returns in decision function. In the order flow model, the algorithm uses differences in the order flow to predict the order flow in the future. The rationale behind the attempt to predict order flow and that way form a decision of the short/long position is the idea of the strong dependence of the
spot exchange rate and order flow. However, the relation between spot rate and order flow is not as evident as the relation between returns and spot rate. In the order flow algorithm the decision estimate is mainly based on adaptive, moving average of the differences in order flow.

\[ F_t = \tanh(u F_{t-1} + v_0 o_t + v_1 o_{t-1} + \ldots + v_m o_{t-m} + w) \]  (7)

where \( o_t \)'s are differences in order flow at \( t \), i.e. how much cumulative buying/selling pressure is changed in time \( t \), \( F_t \) is the decision and \( u, v, w \) are system parameters.

To generalise decisions and to ensure differentiability of the decision, hyperbolic tangent is used. Even though the function is continuous, decisions are discrete and achieve three different positions; long, neutral and short \(([1,0,-1])\). Continuous decisions could be used to measure the strength of the impact, which is based on the variation of the exchange rate. The differentiability of the decision function is important when considering gradient-based optimization of system parameters. The wealth of the trader is defined as the sum of periodic increments.

\[ W_T = \sum_{t=1}^{T} R_t \]

\[ R_t = \mu (F_{t-1} - \delta|F_t - F_{t-1}|) \]  (8)

where \( W_T \) is the wealth of the trader, \( R_t \) is the periodic increment in wealth, \( \mu > 0 \) is the trading position size, \( \delta \) is the transaction cost, and \( r_t \) is the return in period \( t \).

To measure the performance of the algorithm, a utility function of the trader is defined as a function of wealth and profit \((W_T, R_t)\). Strictly speaking the measure of the performance is not a utility function in the conventional sense. The differential ratio, like the Sharpe ratio, is used as a performance measure for the algorithm. Another possible measure is the Sterling ratio. The differential ratio is used to capture the marginal utility of the \( R_t \) in each period. In the algorithm the downsized deviation, which is based on the Sterling ratio, is used as the risk adjusted performance measure for the system parameter update.

\[ Sterling \text{ ratio} = \frac{Annual \ Average \ Return}{Maximum \ Drawn \ - \ Down} \]  (9)

Downsized deviation ratio is

\[ DDR_t = \frac{Average(R_t)}{DD_T} \]

\[ DD_T = \left( \frac{1}{T} \sum_{t=1}^{T} \min\{R_t, 0\}^2 \right)^{1/2} \]  (10)

In order to use the DDR in the recurrent learning, it has to be differentiated. The learning is defined as the gradient of the utility with respect to the system parameters.
\[
\frac{dU_T}{d\theta} = \sum_{i=1}^{T} \left\{ \frac{dR_i}{dF_i} \frac{dF_i}{d\theta} + \frac{dR_i}{dF_{i-1}} \frac{dF_{i-1}}{d\theta} \right\}
\]

(11)

Using gradient learning with learning rate \( \rho \), the adjustment of the parameters is

\[
\Delta \theta = \rho \frac{dU_T(\theta)}{d\theta}
\]

(12)

Note that due to the inherit recurrence of the total derivatives, the entire sequence depends on the previous time periods. To correctly compute the learning in a time sequence, we have to compute in a recursive manner. The learning equation has a form

\[
\Delta \theta_i = \rho \frac{dD_i}{dR_i} \left\{ \frac{dR_i}{dF_i} \frac{dF_i}{d\theta_i} + \frac{dR_i}{dF_{i-1}} \frac{dF_{i-1}}{d\theta_{i-1}} \right\}
\]

(13)

where \( D_i \) is a differential of DDR.

The other algorithm, which uses direct information from the order flow, is a hybrid algorithm that uses a combination of the decision suggested by normal RRL algorithm and order flow based moving averages. In the simulations we decided to use the moving average of the five last observations. The decision is based on heuristic tests of the performance of the algorithm. However, it can be reasoned that if the intraday trading happens with high frequency, then the 5 minute time marginal can be seen as a practical time period. The algorithm combines the information from various subalgorithm parts and makes decisions based on that information. The most obvious advantage of this algorithm is that by combining information from multiple sources, it reduces the risk of biased one source decision. In this hybrid algorithm, the order flow part determines the possible future direction of the spot exchange rate, if we accept the positive correlation assumption between the order flow and spot nominal exchange rate. The RRL part gives estimates not only of the amount of change in spot exchange rate, but also some estimate of the direction.

The combined model of the RRL and order flow is more promising than the use of direct RRL based on the order flow algorithm. The decision function in RRL made it possible for us to utilise order flow more accurately, though different functional forms were thought and tested.

6. Quantitative Analysis of the Performance

The quantitative analysis is performed with simulated data and to some extent with real daily data (Evans and Lyons (1999)). Even though using the daily data somewhat changes the nature of the trading, which is done by algorithms, the algorithms are unrelated to the time discretion of the market time.

To measure the performance of the algorithms, three measures are used; profit, Sharpe ratio, and daily ranking, which is made by ranking analysed algorithms by the daily profit (profit made in daily trading taking place between 0900-1700 i.e. in 480 minutes). Sharpe ratio is defined as
\[ S_t = \frac{\text{mean} \ R_t}{\sqrt{\text{var} \ R_t}} \]  

(14)

where \( R_t \) is the return in time \( t \).

The simulations are done with a set of simulation parameters, where the spread for the day is 0.005. The spread is large, but can be seen in highly volatile markets (i.e. RUB). Half of the used spread is used as the transaction cost for trading. High spreads, like the one used, should encourage algorithms to do fewer trades during the day. Large spreads are also used to encourage gaining differences in simulation results. The tested algorithms have each approximately 5% share of the total order flow of the market. The algorithms can be seen to represent major players in the market (10th largest overall currency trader by volume in May 2008 did have about a 3% share of the overall volume (Euromoney FX survey)). The parameters that define the relation between order flow and spot exchange rate are the order of magnitude of the net order flow of 10 million, which will cause a 1% change in spot rate according to the buying pressure of the demand. The magnitude of the relation is overestimated to find possible changes in exchange rate. Based on this, the volatility of the market is high. In the simulation, the spot exchange rate is updated every minute. However, the macro part of the exchange rate prediction is updated only every 200 minutes (about once in every 3 hours). It can be seen that the changes in macro fundamentals have a lower frequency.

The model parameters in RRL-based algorithms can greatly affect the performance of the algorithm. We should keep this in mind when considering the performance of RRL-based algorithms. The model parameters, like the learning rate and numbers of differences that is used in the moving average part of the decision function, will greatly affect the performance of the algorithm. In the simulation, the RRL model parameters are heuristically chosen and have a high likelihood of not being the optimal ones. The choice of the optimal model parameters for RRL based algorithms can be seen as one of the drawbacks of using these algorithms.

7. Results

The simulation results are based on 10000 simulation runs of the simulation trading day (480 min = 8 hour trading day) to obtain statistically significant results. It took a total of two days to compute these simulation runs. First we look at the results without any filtering or removal of biased observations. Then ten best and ten worst daily results are removed from each algorithm’s result. To analyse the performance of the algorithm, the Kruskal-Wallis non-parametric one-way analysis of variance test (Gibbons, J. D) is performed. The common descriptive statistics of the profits are:
**Table 1.** Profits of the different algorithms. (Profits are measured as percents and 1 means that the equity of the dealer has not changed during the day. Exceptionally high magnitude of $10^3$ profits or loses are explained by the simulation spot exchange rate, which gives a slight possibility to gain unrealistically huge variations in exchange rate.)

<table>
<thead>
<tr>
<th></th>
<th>Order flow RRL</th>
<th>RRL</th>
<th>RRL+Order flow indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>min</td>
<td>-1.7103e+04</td>
<td>-3.6174e+03</td>
<td>-0.5113</td>
</tr>
<tr>
<td>max</td>
<td>5.5840e+03</td>
<td>1.5915e+04</td>
<td>2.2991e+04</td>
</tr>
<tr>
<td>mean</td>
<td>-84.1184</td>
<td>67.1762</td>
<td>165.8828</td>
</tr>
<tr>
<td>median</td>
<td>-2.4319</td>
<td>2.6998</td>
<td>13.1800</td>
</tr>
<tr>
<td>std</td>
<td>683.0393</td>
<td>519.0510</td>
<td>873.0809</td>
</tr>
</tbody>
</table>

In Table 1 we see the descriptive statistics of algorithms, the RRL + order flow indicator and RRL performed well. However, the order flow based RRL had the highest overall result when there was no removal of the 10 best daily results. The highest result was in the order of magnitude of $10^6$. However, this kind of result was caused by exceptional variation of the exchange rate. The fluctuation of exchange rate is an inherit effect of the chosen model parameters, which were chosen to encourage exchange rate variation. It is, however, noteworthy that the RRL + order flow indicator has also the biggest standard deviation. This can be seen as an undesirable characteristic for a good algorithm. On the other hand, RRL seems to perform averagely with a rather small standard deviation.

![Box-Whisker Plot of the profits. (1 is the order flow RRL, 2 is RRL, 3 is RRL + order flow indicator)](image)

**Figure 3** Box-Whisker Plot of the profits. (1 is the order flow RRL, 2 is RRL, 3 is RRL + order flow indicator)
Based on the Kurskal-Wallis test, we can reject the null hypothesis of the same median of all three algorithm’s profits with confidence of 95%. By continuing testing, we can see that even the medians of the RRL and RRL + order flow indicator differ from each other. We can conclude that the RRL + order flow indicator seems to outperform the others.

**Table 2.** Sharpe ratio descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Order flow RRL</th>
<th>RRL</th>
<th>RRL+Order flow indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>min</td>
<td>-0.2782</td>
<td>-0.0926</td>
<td>-0.2385</td>
</tr>
<tr>
<td>max</td>
<td>0.8011</td>
<td>0.1686</td>
<td>0.2628</td>
</tr>
<tr>
<td>mean</td>
<td>0.0301</td>
<td>0.0393</td>
<td>0.1283</td>
</tr>
<tr>
<td>median</td>
<td>-0.0070</td>
<td>0.0395</td>
<td>0.1407</td>
</tr>
<tr>
<td>std</td>
<td>0.1661</td>
<td>0.0407</td>
<td>0.0694</td>
</tr>
</tbody>
</table>

**Figure 4** Sharpe ratios (Ratios of each individual simulation day sorted in descending order)

Table 2 and in Figure 4 show that the order flow RRL performs both exceptionally well and very poorly with respect to the Sharpe ratio. This is especially evident in Figure 4 where the line of the order flow RRL is very S-shaped when compared to the other algorithms. We see that the RRL stays rather flat with respect to the Sharpe ratio and therefore its performance is steady, if not the most profitable. RRL + order flow indicator seems to perform well in general, but does have some bad days. To summarize, we can conclude that RRL+ order flow indicator is in a class of its own in general. The RRL performs most steadily. The order flow RRL does have some remarkable days, but the overall performance is not good.
**Figure 5** Daily ranking of the algorithms (From left: number one rankings, number two rankings, number three rankings)

Figure 5 shows that RRL + order flow indicator captures most of the top rankings. RRL has a consistent performance and ranks number two in most of the days. Order flow RRL seems to be the option with the weakest performance.
We can see a noteworthy trend in Figure 6. The order flow RRL outperforms the rest of the algorithms. This is mainly due to the more cautious nature of the RRL + order flow indicator, which can be seen in the decisions panel (Figure 6, third panel from the top), where there are many zero decisions made by RRL + order flow. Looking at the Sharpe ratio panel, we can see that order flow RRL algorithm at all times performs well and that other algorithms perform horribly. In order to gain more realistic and statistically correct results, more genuine minute data would have been needed. The parameterisation of the RRL-based algorithms can also be seen as a relevant factor, since the model parameters for RRL were chosen to represent a volatile simulation market. The effects of the parameters are most clearly seen in the RRL + order flow indicator algorithm; the algorithm is too careful and therefore makes too many zero decisions (Figure 6, third panel). However, since limited genuine data was available for the RRL model parameters, we were unable to choose them in any more specified way.

8. Limitations of the Simulation

The simulation is somewhat simplified. We were forced to determine some simulation parameters, namely parameters for distributions of the order flow, size of the market, and segmentation of the different algorithms. From the algorithm point of view, one limiting factor was the choice of the model parameters. The lack of a limit order book can be seen as a hindrance in the simulation model. The realistic implementation of a limit order book is difficult, because in order to define it realistically, we would need to know the traders’ strategies of using to use the limit order book. There are several ways to use the
limit order book; it can be used as a risk control method as well as in an opportunistic way. The simulation was based on only a limited number of agents and the rest of agent population was modeled only with distributions.

9. Conclusions
The use of the order flow information and better understanding of the FX market help develop better trading algorithms. However, the efficient utilisation of the gained information seems to be hard. The hybrid algorithms are the most promising approach to construct a well-performing algorithmic trader. The better understanding of the market microstructure helps us to develop more accurate indicators and hence, to improve algorithmic trading. Based on the simulations presented in this paper, the order flow information helps us to develop better algorithmic traders. However, constructing an efficient algorithm remains a challenge. Algorithms implemented like the RRL are black box models. These algorithms are very sensitive to model parameter changes. The prospect of RRL-based algorithms being able to learn to pick certain features in the FX market and to make defeasible decisions based on those features is promising. In order to gain better and more accurate results, genuine minute-based data is needed. It might be available in some time in the future mainly because of the advances in algorithms and the transition to use electrical broker systems (e.g. EBS).

The next logical research challenge is to develop an even better and detailed understanding of the market microstructure. After that we might see the use of new kinds of algorithms, e.g. Hidden-Markov process based algorithms, which are used with success in speech recognition. In the future it is interesting to see whether the use of algorithmic trading will alter the dynamics of the market and exchange rate process, or not.
10. References


Feng Wang, Xiao-Bing Feng, Lu Tang, Microeconimic Modeling and Simultion of Exchange Rate with Heterogeneous Strategies, Proceedings of the Sixth International Conference on Machine Learning and Cybernetics, Hong Kong, 19-22 August 2007


Euromoney FX survey FX Poll 2008: The Euromoney FX survey is the largest global poll of foreign exchange service providers.' (wikipedia) (http://www.euromoney.com/Poll/3301/PollsAndAwards/Foreign-Exchange.html) (27.1.2009)