A Model for Trading the Foreign Exchange Market

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Abstract

The electronic Foreign Exchange (FOREX) market where currencies are bought and sold has become more complex and dynamic with characteristics of high volatility, nonlinearity, and irregularity. Some important factors such as economic growth, trade development, interest rates, inflation rates, etc. have significant impacts on the exchange rate fluctuation. Existing foreign exchange (FOREX) trading models have been found inadequate. They have tended to use only past price data and appear to be too stochastic or too deterministic. In this work an improved model that provides a wide set of dynamic process information has been developed. Technical and fundamental methods of analysis of FOREX market data were modeled with neural networks. The predictions from the networks are integrated to get the direction of price movement. Market sentiment and volatility values are combined with the neural network prediction to develop trading strategies using Marcov chain. Finally, an application of the model in FOREX trading is demonstrated and implemented with the Meta-Quote scripting Language (MQL) of the meta-Trader platform. The historical test of the robot for the last 12 months resulted in a range of significant profitability with annual returns between 40% to700% and with maximum relative draw down risk between 8% to 52%

Keywords: FOREX, marcov chain, model, neural network, trading robot

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Introduction

Electronic currency trading in the Foreign Exchange (FOREX or FX) market is now a very popular activity. FOREX is the single largest market in the world accessible to anyone. Its volumes are greater than all stock, commodities and debt markets combined [1]. Average daily foreign-exchange volume rose to $3.873 trillion in October 2013, from $3.604 trillion in the previous October, according to reports published by the Bank of International Settlements in the first phase of its triennial findings for its three yearly global FX survey. [2] attributes the sharp increase in FX activity to several factors including; market volatility, acceptance of FX as an asset class and global distribution of the product. Cyril Tabet, Partner & CEO at JFD Brokers, believes the quality of the end product will have a direct impact on volumes, and explained in a comment to Forex Magnates: "Sustaining high standards in technology, execution, transparency, and support have proven to significantly drive volumes up."

The market is open day and night from Sunday night to Friday night. The development of trading models is challenging as the problem of figuring out proper input and output values that derive long term profitable results is not simple. Consistently predicting FX markets has seemed like an impossible goal but recent advances in financial research now suggest otherwise. With newly developed computational techniques and newly available data, the development of successful trading models is now possible.

Many economic variables (including interest rates) have little explanatory power at high frequencies. Many traders have therefore used technical analysis. Technical analysis attempts to predict markets by identifying patterns (Channel, Head and shoulder, Cup and handle, etc.) in the price actions. Developing optional trading models by combining a number of technical, fundamental, sentiment and informational indicators to predict volatility and directionality reduces failure in changing conditions. The complexity of the financial price behaviour is often so high as if it looks like intractable, or one could assume no such complexity exists as expressed by the Efficient Market Hypothesis (EMH). The debate on the market efficiency has a long history which has resulted in no confirmative conclusions. Nonetheless, with so much empirical observations and numerical tests conducted on the financial market price distributions, quantitative financial researchers and professional analysts have reached a consensus view that the markets are dynamic, and always swing between the efficient and inefficient regimes and modes [3]. Therefore, dynamic structural patterns do appear existent from time to time with a temporary and fleeting nature and perhaps also with highly abstract invariances. Separating different aspects of the market when making predictions is important as it leads to profitable trading setups. Thus a co- integration (COINT) model that incorporates technical, fundamental, sentiment and news is proposed to optimize profit subject to risk considering real world trading constraints.

Literature Review

Many new models have been developed, such as agent-based simulation models of financial markets [4], evolutionary computing – neural networks and genetic algorithms [5] as well as swarm intelligence [6] and fractals of complex dimensions. Geometric Brownian Motion (GBM) by [7]) is one of the earliest most popular models. It is a model of the Efficient Market Hypothesis (EMH) with little dynamic components like stochastic trend. The model is uncertain when faced with the volatility of the market prices as measured in terms of annualized standard deviation of the market prices. The notion of volatility as measured by standard deviation or variance has become a focus of attention in quantitative finance, which led to a plethora of research streams such as implied volatility, volatility smile and volatility surface in option pricing, ARCH and GARCH type of models for volatility dynamics, and value at risk as a measure of risk exposure under any given volatility distribution [8].

The Log-Periodic Power Law (LPPL) is a nonlinear regression model for aggregate market prices developed by [9] and his associates since 1996. The LPPL is used for financial bubbles and its counterpart – anti-bubbles. The duality of financial bubble and anti-bubble corresponds to a far-from-equilibrium state process of the market, which cannot be captured by the GBM-type models under the EMH.

These two models – GBM and LPPL – represent the two extreme types of financial market price models: the GBM is extremely stochastic, while the LPPL is extremely deterministic. This duality of over stochastic versus over-deterministic models reminds us of the existence of a big gap in modeling the financial market prices. It naturally points out a need to find or devise a modeling structure which is useful to explore more general stochastic and dynamic patterns of the market prices between these two extremities. The model proposed in this work is intended to serve this purpose. However relying on just financial time series price data may not be sufficient as there are several other factors that might contribute to market fluctuations. Financial markets are sensitive to economic news but are also influenced by a wide variety of unanticipated events. While the market can react strongly to some news, it could remain completely insulated from other financial news.

Trading Models

The ARGARCH Model

The AR(p)-GARCH(1,1) process is written as

$$r_t = \gamma + \sum_{i-1}^{p} \gamma_i r_{t-i} + \epsilon_t \quad (1.0)$$

Where $\epsilon_t = h_{tztzt}^{1/2}$ ~N(0,1) and $h_t = a_0 + a_1 h_{t-1} + \beta_1 \epsilon_{t-1}^2$. The estimated parameters of the AR(p)-GARCH(1,1) processes together with the simulated residuals are used to generate the simulated returns from these processes [10]. Half of the average spread is subtracted (added) from the simulated price process to obtain the simulated bid (ask) prices.

Exponential Moving Averages with Robust Kernels

The moving average indicators are used to summarize the past behavior of a time series at a given point in time. In many cases, they are used in the form of a momentum or differential, the difference between two moving averages. The moving averages can be defined with their weight or kernel function. The choice of the kernel function has an influence on the behavior of the moving average indicator. A particular type of moving average called exponential average plays an important role in the technical analysis literature. Exponential moving average (EMA) operator is a simple average operator with

$$w_{ema}(t; r) = \frac{e^{-t/r}}{r} \quad (1.1)$$

an exponential decaying kernel. r determines the range of the operator and t indexes the time. An EMA is written as

$$EMA_p(r, t) = \int_{-\infty}^{t} w_{wma}(t - t^{'})p(t^{'})dt^{'} \quad (1.2)$$

where

$$w_{ema}(t - t^{'}; r) = \frac{e^{-(t-t^{'})/r}}{r} \quad (1.3)$$

The Real Time Trading (RTT) Model

The real-time trading model traces the market trend and opens position when a certain threshold is reached. The model identifies an overbought/oversold situation during market movement and recommends taking a position against the current trend. This strategy is governed by rules that take the recent trading history of the model into account. The RTT model goes neutral only to save profits or when a stop-loss is reached. The gearing function for the RTT is

$$g(I_p) = sign(I_p) f(|I_p|) c(I) \quad (1.4)$$

where

$$I_p = p - MA_p^4(r = 20) \quad (1.5)$$

Where p is the logarithmic price and

$$f(|I_p|) = \begin{cases} if\ |I_p| & > & b & 1 \\ if a < |I_p| & < & b & 0.5 \\ if\ |I_p| & < & a & 0 \end{cases} \quad (1.6)$$

and

$$c(I) = \begin{cases} +1 & if |I_p| < d \\ -1 & if |I_p| > d \end{cases} \quad (1.7)$$

where $a < b < d$. $f(|I_p|)$ measure the size of the signal and $c(|I_p|)$ acts as a contrarian strategy.

and b are functions of current position, volatility and trading frequency. d is a function of position in, previous position, sign of the return of the previous position. The model is subject to the open-close and holiday closing hours. The model has maximum stop-loss and maximum gain limits set by the environment.

Support Vector Machine (SVM) Regression Model

[11] used SVM based models for predicting currency rates. SVMs formulate

the regression problem as a quadratic optimization problem. They perform a nonlinearity mapping of the input data into a high dimensional feature space by means of a kernel function and then do the linear regression in the transformed space. The whole process results in nonlinear regression in the low dimensional space. Given a data set.

$$G = \left\{ \left(x_i , y_i \right) \right\}_{i=1}^{N} \qquad (1.8)$$

A function *f* is determined that approximates *g(x)* based on the knowledge of *G* as shown in (1.8)

$$f\left(x\right) = \sum_{i} \omega_i \varnothing_i \left(x\right) + b \qquad (1.9$$

Where $\varnothing_i\left(x\right)$ are the features, coefficients ω_i and *b* have to be estimated from data.

The limitation in SVM based models is that the choice of kernel function is based on pattern behavior of historical rates of individual currency.

Geometric Brownian Model

Financial investment returns are geometric in terms of percentage instead of arithmetic change. According to [7] the expected percentage return required by investors from a financial asset is independent of the asset's price. Let *S* denote the price of an asset, the geometrical Brownian motion (GBM) as a stochastic model of the asset price is defined as

$$dS = \mu S\, dt + \sigma S dW \qquad (2.0)$$

where μ is the drift rate (percentage drift) and σis variance rate (percentage volatility) . Whenμand σare constant, for an arbitrary initial value S_0, the differential equation of GBM (2.0) has the analytic solution

$$s_t = s_0 \exp\left[\left(\mu - \frac{\sigma^2}{2} \right) t + \sigma W_t \right] \qquad (2.1)$$

From equation (3.32),$S_t$is a log-normally distributed random variable

$$S_t \;\Box\Box \left[S_0 e^{\mu t}, S_0^2 e^{2\mu t} \left(e^{\sigma^{2t}} - 1 \right) \right] \qquad (2.2)$$

The GBM as expressed in equation (2.0) provides a simplistic model for financial asset price returns as it only contains a linear trend – the percentage drift component μwhile the rest is a Brownian motion. In terms of the original asset prices, the trend modeled is rather geometrical (exponential) with fixed parameters –μandσ.

The forex rate *S* is defined by two currencies – foreign versus domestic. The GBM model for a forex rate takes the form:

$$dS = \left(r_d - r_f \right) S_t dt + \sigma S_t dW \qquad (2.3)$$

wherer_d and r_f denote the (continuous) foreign and domestic interest rate respectively, and σdenotes the volatility. Similar to equation (2.1), the solution for the forex rate *S* can be derived as

$$S_t = S_0 \exp\left[\left(r_d - r_f - \frac{\sigma^2}{2} \right) t + \sigma W_t \right] \qquad (2.4)$$

The GBM as a mathematical model of the financial market prices does not express the reality of the financial market price behaviours as we know it today. It suffers from two major shortcomings: (1) it is too simplistic and incapable to express the rich variety of stochastic-dynamic patterns in the price behaviours such as trendlines, trend channels, support and resistance, waves and bubbles on multiple time scales; (2) it does not provide information variables to connect to market and economic information sources

Modeling the FOREX process

Trading models emulate the trading conditions of the real foreign exchange market as closely as possible. They do not deal directly but instead instruct human foreign exchange dealers to make specific trades. The central part of a trading model is the analysis of the past price movements which are summarized within a trading model in terms of indicators. The indicators are then mapped into actual trading positions by applying various rules. For instance, a model may enter a long position if an indicator exceeds a certain threshold. Other rules determine whether a deal may be made at all. Among various factors, these rules determine the timing of the recommendation. A trading model thus consists of a set of indicator computations combined with a collection of rules. The former are functions of the price history. The latter determine the applicability of the indicator computations to generating trading recommendations.

A currency P can be modeled in terms of a technical information set α_P extracted from its own timeseries ($P(t)$, $P(t-1)$,...), an economic information set β_P including the interest rate r_p and other selected economic/sentiment indicators and financial indexes which are influential to P, and an information set extracted from impacting news μ_P including scheduled sn_P and unscheduled un_P. For any 2 given currencies P, Q we have a minimal set of dynamic models as

$$
\begin{aligned}
P(t+\lambda) &= F_P(\alpha_P(P(t), P(t-1), \ \beta_P(\gamma_P,\ldots), \ \mu_P(sn_P, un_P)) \qquad (2.5)\\
Q(t+\lambda) &= F_P(\alpha_P(Q(t), Q(t-1), \ \beta_P(\gamma_P,\ldots), \ \mu_P(sn_P, un_P))
\end{aligned}
$$

Where λ is how far into the future the prediction is supposed to be. If $[PQ]$is the exchange rate of P to Q, which is actually observable from the forex market, then we have the equation

$$P(t)/Q(t) = [PQ](t) + \mathcal{E}_{PQ} \qquad (2.6)$$

Where $\mathcal{E}$ is the error term. The two sets of equations 2.5- 2.6 provide a framework for modeling currencies integrating technical, fundamental, sentiment and news information and observable forex market data. There are many possible component models for each of technical, fundamental, sentiment and news aspects and also for the interplay of these aspects. Artificial Neural Networks was used to analyze and predict the technical aspect with special interest on volatility and market sentiment.

Market Sentiment

Market sentiments play an important role in determining currency values. These directly influence demand and supply within the market [12]. During times of global economic unrest, values will increase for stronger currencies which are linked to countries viewed as stable. A country whose inflation levels are high will be viewed as a poor prospect for forex trading because future economic growth is likely to be hampered by high prices. Investors' perception of an economy and interpretation of various economic indicators determine the overall market sentiment for a currency.

Neural Network Based Forex Model

Neural networks are of particular interest because they offer a means of efficiently modeling large and complex problems in which there may be hundreds of predictor variables that have many interactions. Neural networks (figure 1.1) starts with an input layer, where each node corresponds to a predictor variable. These input nodes are connected to a number of nodes in the hidden layer. Each input node is connected to every node in the hidden layer. The nodes in the hidden layer may be connected to nodes in another hidden layer, or to an output layer. The output layer consists of one or more response variables

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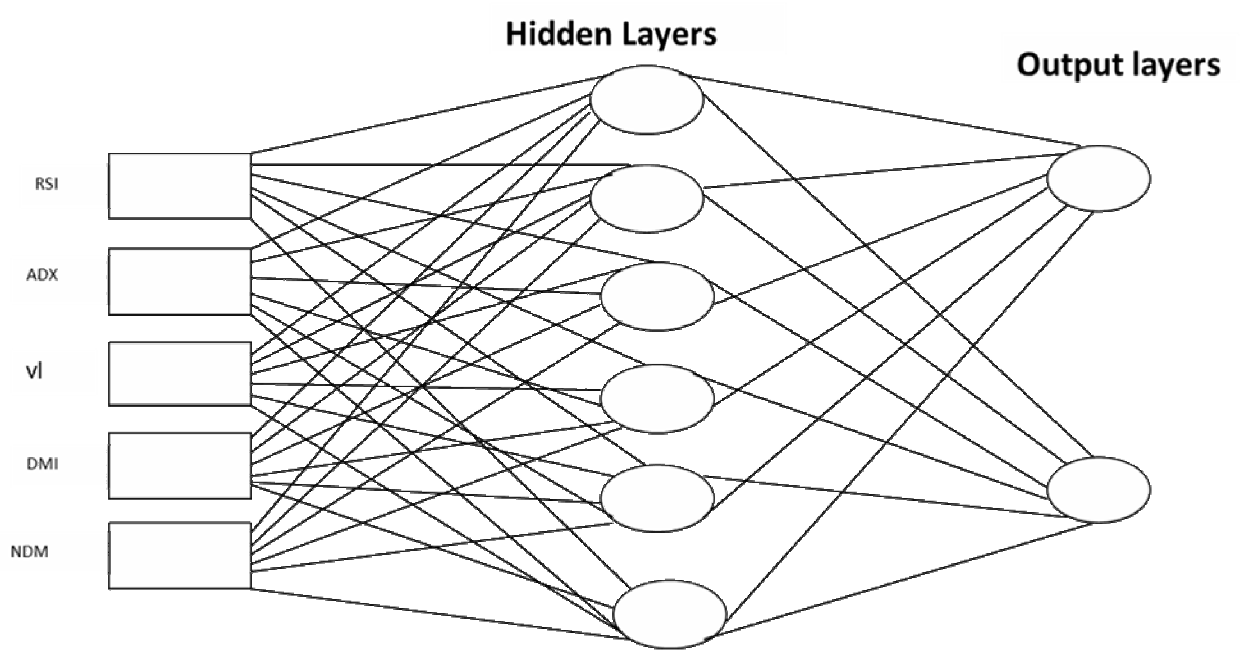

Figure 1.1: Neural network architecture

The three layers feed forward network can be represented by the following expression:
$Y=\lambda 0+\Sigma\lambda j\times\Phi j(wj\times x)$

Where
y is the output,
x is a vector of inputs,
Φj is a series of functions (typically logistic or hyperbolic tangents),
Wj is a series of weight vectors to ensure that each Φj receives a different input, λ0 a constant, and λ1 to λM a series of weights that weight the outputs from Φ1 to ΦM.

The neuron mathematical model is represented by three basic components as shown in figure 1.2:

- **weights,**
- **adder** sums up all the inputs modified by their respective weights.
- **activation function** controls the amplitude of the output of the neuron

Model Application Design

The system design which is most creative and challenging refers to the technical specifications and procedures that will be applied in implementing the model. It also includes the construction of programs and program testing. The architecture of the system from input through processing to output is shown in figure 1.3 while the high level design is shown in figure 1.4

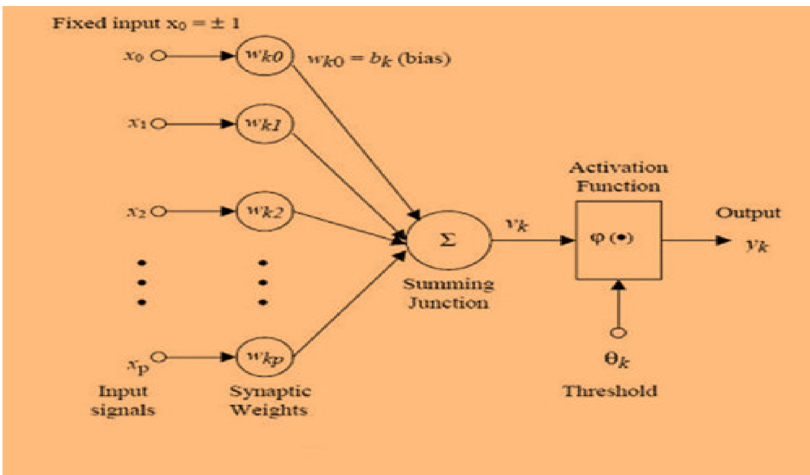

Figure 1.2: Neuron components

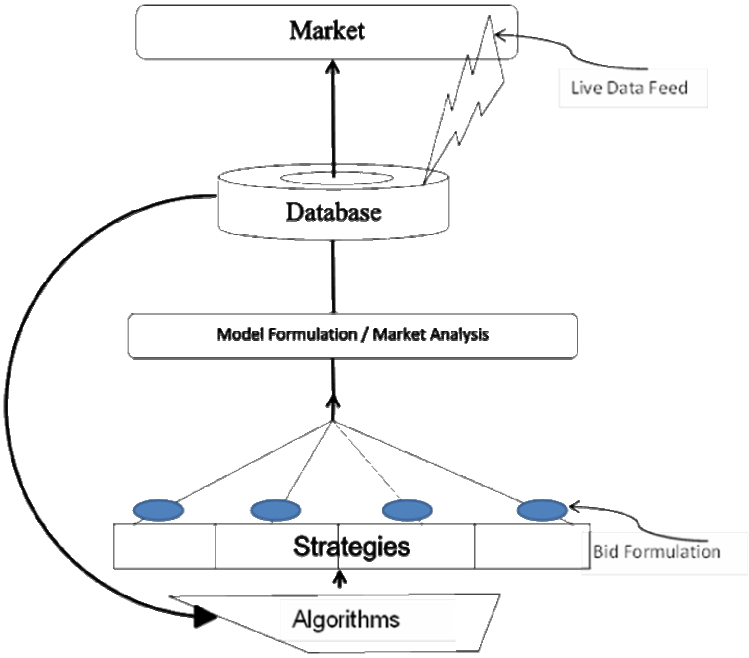

Figure 1.3: Trading system Architecture.

High level design

The proposed system consists of five Phases: data collection and preprocessing, the neural network prediction, the neural indicator, filtering/integration strategies and the trading system decision. The road to a more reliable financial market analysis process begins with a more comprehensive set of market data available through trading servers in the internet. Technical data sets are extracted with a data collector program and stored in excel file for preprocessing. Data is normalized and fed to the neural network for training and testing so that the network can learn the dependencies and apply those dependencies when presented with new data. From there the network can compare its own output to see how close to correct the prediction was, and go back and adjust the weight of the various dependencies until it reaches the correct answer. Since the predictions from the neural network most times produce unprofitable trades, filtering techniques which include genetic algorithm are used to select the best. The generation of profitable trading rule for currency trading is a difficult problem. Integration and network combination strategies are used to produce profitable trading system which is tested using the strategy tester of MetaTrader 4. It is then deployed on a virtual demo account for live trading.

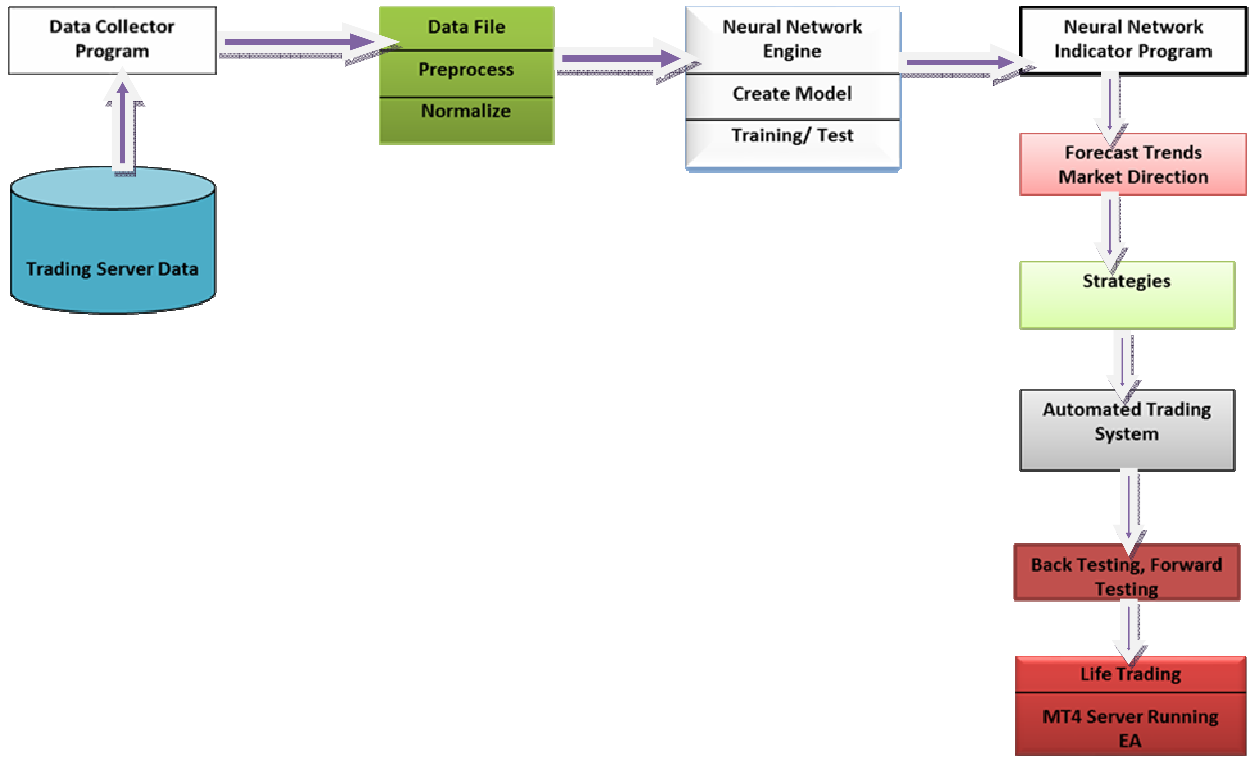

Figure 1.4: High level design

Implementation

Automated trading systems have three functions, viz., money management, risk control and market analysis. Money management is a part the of investment strategy. In forex trading, money management is used to set the capital amount for each transaction. The risk control function helps traders set a stop and loss level, and it is able to delete transactions that go in the opposite direction from the current market. The analysis function is used to capture trading opportunities, and it is always programmed by a variety of trading methods. However, most trading robots cannot capture all the market sentiments, and the historical data cannot present all future movements. The major factor that causes trading robots to make mistakes is the nature of the forex market.

The principle of multi-aspects design of trading systems contributes to the systematical and comprehensive solution of the trading system creation task. Figure 1.5 contains the Trading System block and its interactions. Open position and Close position controls when and at which price you open and close your trades. A trading system operates on the signals generated by the neural network. The signals are processed to determine if the trader should buy or sell a particular currency pair or should close the existing position(s). Manage risk checks the value of the opened trades in relation to the account balance. It constantly monitors the equity of the trading account and prevents costly drawdowns by closing half the volume of all loosing accounts (22% drawdown or by closing all loosing accounts completely (33% drawdown). Profit protects the capital base and the unrealized profits. The capital base is protected by ensuring that the trades are exited with a fixed loss when the reasons for holding them are no longer valid. This is done by triggering a *stop-loss* order on the forex brokerage account when the price crosses the level which defined risk at the entry. The unrealized profits are protected either by a *take-profit* order which is triggered on the brokerage account when the price reaches the level which defined profit at the entry or with the help of the *trailing* *stop-loss* which gradually locks in more profits as the price moves in favor

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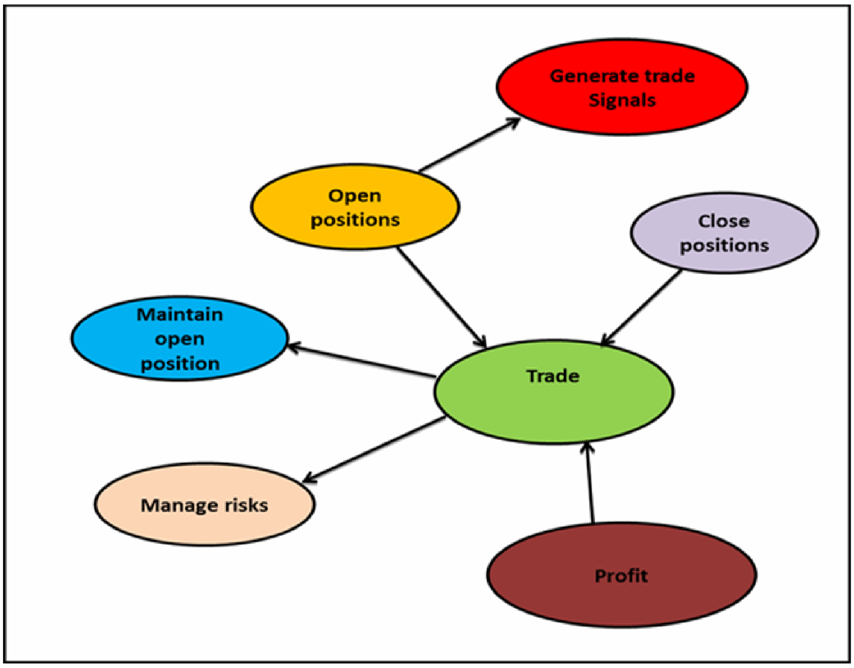

Figure 1.5: Trading system modules

Discussion of Results

Backtesting helps to see how the system would have performed if it was run during some period in the past. Indicator parameters are optimized using the price data in the backtesting period. It is important that the time period the system is backtested on represents the currency pair to trade. It should include all types of market conditions (trending, range bound) and it should be as recent as possible. Once the performance of the system is satisfactory, the forward test is carried out – it is run on the out-of-sample price data (the price data that would be immediate future to the backtesting period). This way the performance of the system is compared with the way it did during the backtesting. The closer the system's performance during the forward testing is to its performance during the backtesting the more robust the system and the more confident we can be that it will continue to trade in a similar manner during the real-time trading. Backtesting was done with Metatrader 4 using EURUSD H1and the profitability graph is shown in figure 1.6 Implementation of the system was done on MetaTrader 4 platform which was used to create the network and design the trading Robot. Testing was done on a demo account and the result presented in figure 1.7 and figure 1.8

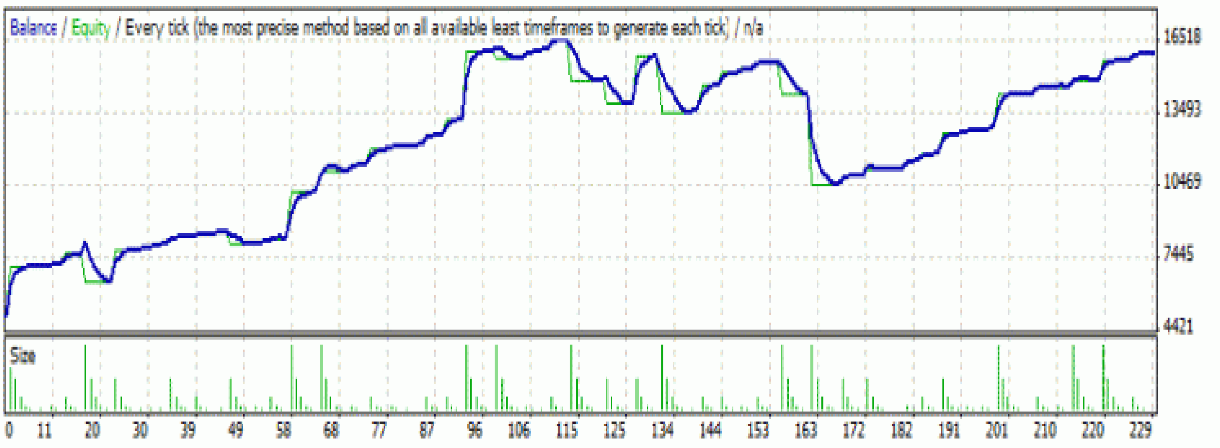

Figure 1. 6: Backtesting profitability Graph

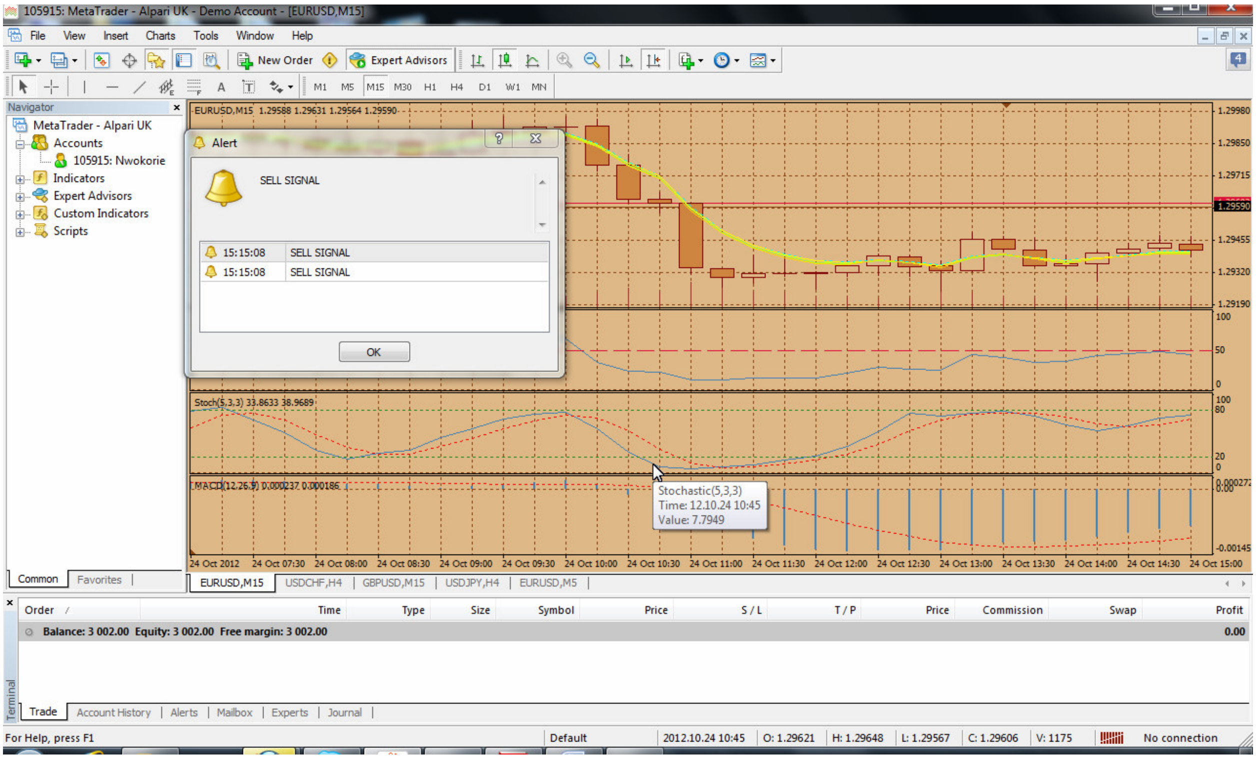

Figure 1.7: sell signal

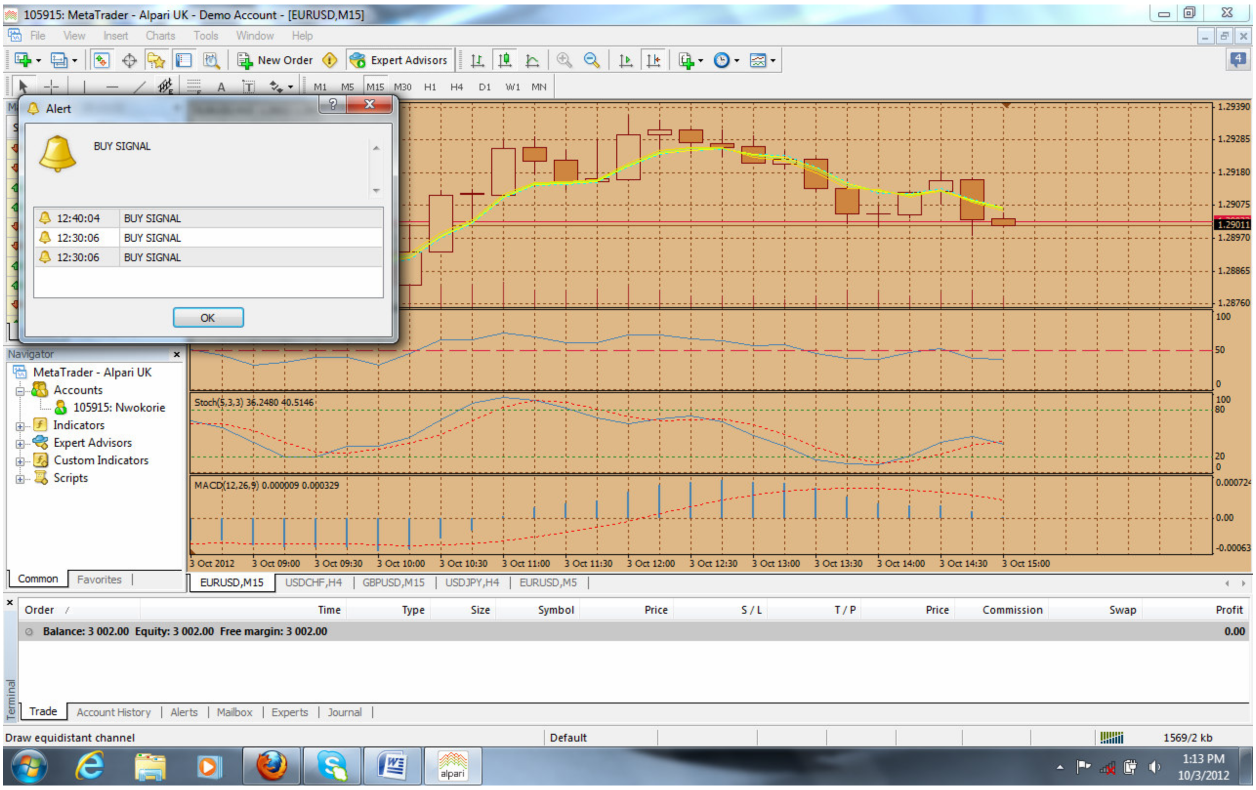

Figure 1.8: Buy signal

Trading Strategies

The built-in Strategy Tester in MetaTrader 4 Trading Platform is used to test how the Trading robot can perform in trading. This powerful tool allows simulated testing of the efficiency of an Expert Advisor and detects the best input parameters before it is used for real trading on the Forex Markets. The trading robot performs virtual transactions on historical data of the financial instrument in accordance to its trading algorithm. The result of virtual trading done from January – December 2014 is summarized in table 1.2 and table 1.2.

Table 1.1: EURUSD Live test Result summary

Initial deposit	10000.00				
Total net profit	458.20	Gross profit	9629.55	Gross loss	-9171.35
Profit factor	1.05	Expected payoff`	4.36		
Total trades	105	Short positions (Won%)	105 (4286%)	Long positions (won%)	0(0.00%)
		Profit trades (% of total)	45/42.86%)	Loss trades (% of total)	60(57.14%)
Largest		Profit trade	955.15	Loss trade	-497.30
Average		Profit trade	213.99	Loss trade	152.86
Maximum		Consecutive wins (profit in money)	5(376.75)	Consecutive losses (in money)	7(-661.75)
Maximum		Consecutive profit (count of wins)	1158.00 (3)	Consecutive loss (count of loss)	-893.15 (6)
Average		Consecutive wins	2	Consecutive losses	2

Table 1.2:GBPUSD Live test Result

Initial deposit	10000.00				
Total net profit	11017.24	Gross profit	24645.85	Gross loss	-13628.62
Profit factor	1.81	Expected payoff`	48.11		
Total trades	229	Short positions (Won%)	110 (70.91%)	Long positions (won%)	119(73.11%)
		Profit trades (% of total)	165(72.05%)	Loss trades (% of total)	64(27.95%)
Largest		Profit trade	1688.88	Loss trade	-212.95
Average		Profit trade	149.37	Loss trade	-1760.35
Maximum		Consecutive wins (profit in money)	12(5151.98)	Consecutive losses (in money)	12(-5238.64)
Maximum		Consecutive profit (count of wins)	5151.98 (30)	Consecutive loss (count of loss)	-5238.64 (12)
Average		Consecutive wins	10	Consecutive losses	4

Comparative evaluation

The comparative evaluation of the model with other models indicated significant improvement as shown in Table 1.3. This is graphically depicted in figure 1.9. The performance measure of the robot is summarized in table 1.4 and figure 2.0. From the table it can be seen that the best relative position size is RPS=0.8 lots / \$10,000, which performed with the best Survival Risk Reward Ratio SRRR = 6.54. It means that for the worst downside risk, the reward – Annual Return of Investment ARI is more than 6 times bigger than that maximum risk.

Table 1.3: Comparative evaluation of the models

Parameter	**GBM**	**GARCH**	**EMA**	**COINT**
Total Net Profit	733.56	348.44	567.62	2658.29
Bal. Drawdown Abs.	0.00	164.22	399.50	534.36
Eq. Drawdown Max.	339.50(3%)	287.60	413.08	625.36 (6%)
Profit Factor	4.72	1.50	1.56	1.55
Recovery Factor	2.16	1.78	1.95	4.25
Expected Payoff	30.5	8.93	15.37	78.08
Sharp Ratio	0.79	0.46	0.52	0.15
Total Trades	24	39	176	329
Total Deals	48	94	275	658
Profit Trades (% total)	21(87%)	24(42%)	45(42%)	187 (56%)
Average Profit Trade	44.33	41.97	21.70	39.95
Average Consec. Wins	5	6	4	2

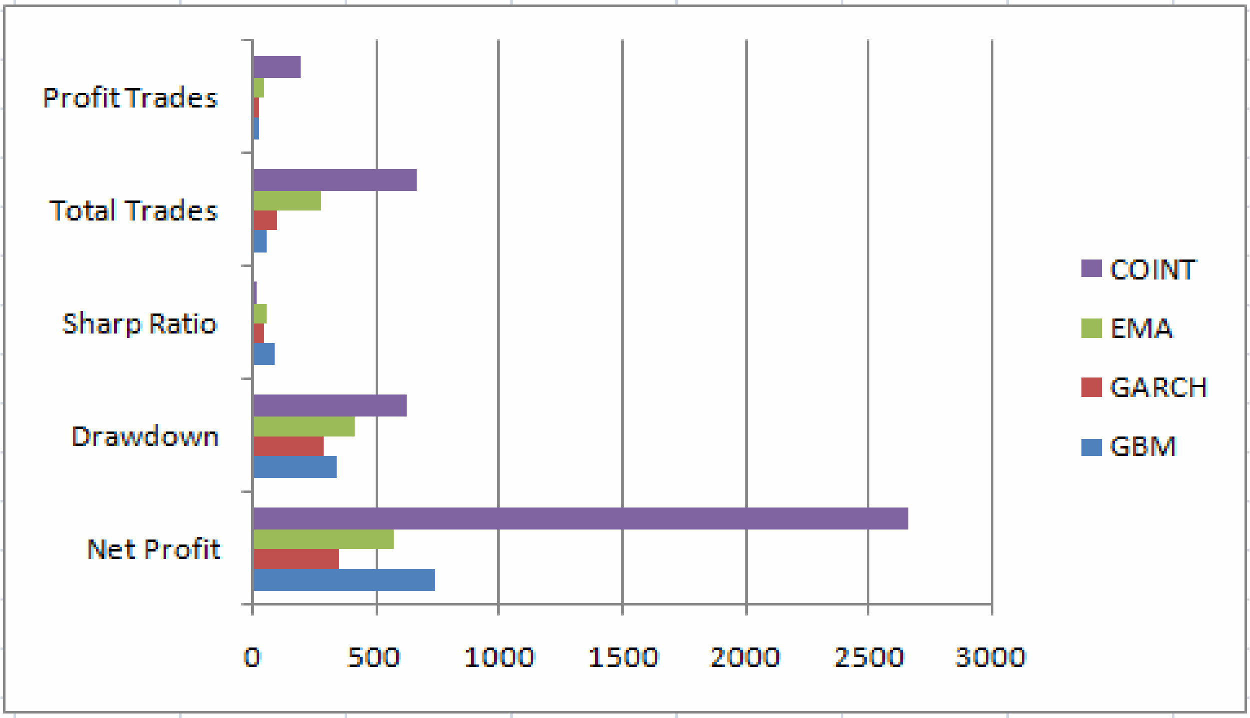

Figure 1.9: Comparative Evaluation with other models

Table 1.4: Performance measure of the Robot

RPS	ARI	MRDD	MSR	CRRR	SRRR
0.1	29.9	6.96	7.48	4.30	4.00
0.2	72.46	13.53	15.65	5.35	4.63
0.3	128.23	19.73	24.58	6.50	5.22
0.4	187.12	25.6	34.41	7.31	5.44
0.5	251.06	30.19	43.25	8.32	5.81
0.6	318.97	37.95	61.16	8.41	5.22
0.7	446.92	41.21	70.10	10.84	6.38
0.8	531.13	44.8	81.23	11.85	6.54
0.9	635.73	49.33	97.36	12.89	6.53
1	706.76	55.25	123.46	12.81	5.73

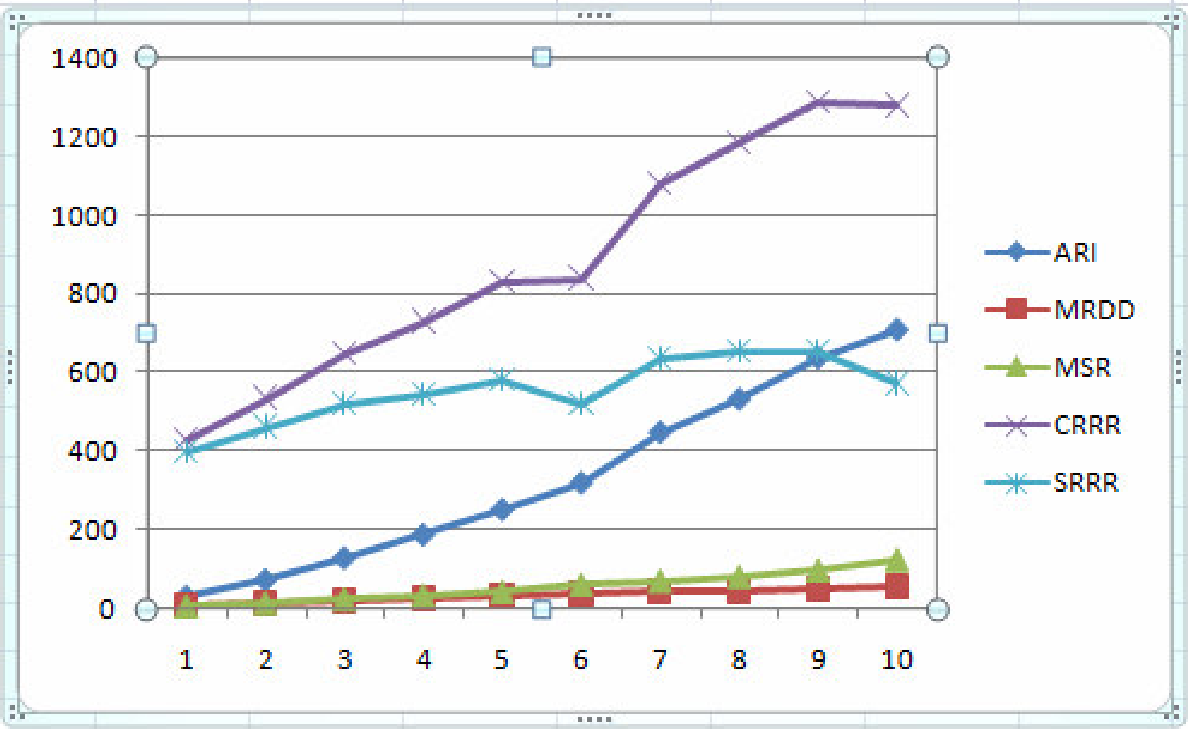

Figure 2.0: Performance measure of the Robot for EURUSD on H1

Conclusion

An improved model that includes more set of dynamic process information about the market prices is proposed. This was done through the addition of new parameters on sentiments and volatility to the existing model. A comparative benchmark with models based on technical data alone showed that the addition increased profit. Using integrated neural networks to analyze, predict and trade currencies in the foreign exchange market also produced better prediction than one. A new strategy using marcov chain that identified eight market phases instead of the usual three has resulted in a range of significant improvement on profitability

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