Evaluation Method of Forex Trading Analysis Tool
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Abstract—FOREX (Foreign Currency Exchange) is concerned with the exchange rates of foreign currencies compared to one another. These rates provide significant data necessary for currency trading in the international monetary markets. FOREX rates are impacted by a variety of factors including economic and political events, and even the psychological state of individual traders and investors. These factors are correlated highly and interact with one another in a highly complex manner. Those interactions are very unstable, dynamic, and volatile. This complexity makes predicting FOREX changes exceedingly difficult. The people involved in the field of international monetary exchange have searched for explanations of rate changes; thereby, hoping to improve prediction capabilities. It is this ability to correctly predict FOREX rate changes that allows for the maximization of profits. Trading at the right time with the relatively correct strategies can bring large profit, but a trade based on wrong movement can risk big losses. Using the right analytical tool and good methods can reduce the effect of mistakes and also can increase profitability.

Data mining involves the use of sophisticated data analysis tools to discover previously unknown, valid patterns and relationships in large data sets. These tools can include statistical models, mathematical algorithms, and machine learning methods. Consequently, data mining consists of more than collecting and managing data, it also includes analysis and prediction.

Keywords—FOREX, Data mining, Option mining.

I. LITERATURE REVIEW

Piche [18] uses a trend visualization plot on a moving average oscillator. For example, he uses an exponential moving average oscillator method to compute the fractional returns and then uses the trend visualization algorithm to plot the trend visualization matrix. By setting different parameters on the currency exchange rates of various national currencies, the results show this method is useful in gaining insight into other aspects of the market.

Staley and Kim [23] have suggested that interest rates are the most important variable determining the currency exchange rates; “self-fulfilling” behaviour may also contribute to the movements in the rates. Therefore, they use two inputs: One relates to the changes in interest rates, and the other is the short-term trend in the exchange rate to search for patterns in the data. They indicate the model could be improved if more variables were added and the results were tested. Additionally, confidence regions (or error bars) could be added to the predictions so more appropriate validation sets could be chosen. This information could suggest whether on not the prediction should be applied on any given day.

Demster, Payne, Romahi and Thompson [7] have shown two learning strategies based on a genetic (programming) algorithm (GA) and reinforcement learning, and on two simple methods based on a Markov decision problem and a simple heuristic technique. All methods generate significant in-sample and out-of-sample profit when transaction costs are zero. The GA approach is superior for nonzero transaction costs. They also state that when in-sample learning is not constrained, then there is the risk of overfitting.

Chen and Teong [4] use a simple neural network to improve regular technical analyses. The result of using a neural network not only enhances profitability but also turns losing systems into profitable ones. This provides one with the opportunity to enter and exit trades before a majority of other traders do. A neural network is also able to adapt itself to new patterns emerging in the market place. This is important because currency market conditions change very rapidly.

Refenes, Azema-Barac and Karoussos [22] demonstrate that by using a neural network system and an error back-propagation algorithm with hourly feedback and careful network configurations, short term training can be improved. Feedback propagation is a more effective method of forecasting time series than forecasting without a feedback neural network. They also considered the impact of varying learning times and learning rates on the convergence and generalization performance. They discovered that multi-step predictions are better than single-step predictions as well as the fact that appropriate training set selection is important.

Laddad, Desai and Poonacha [16] use a multi-layer perceptron (MLP) network for predicting problems. The raw data contained a considerable volume of noise so they decomposed the data into many less complex time series data and used a separate MLP to learn each of them. Another method is to use two new weight initialization schemes. Both methods provide faster learning and improved prediction accuracy. The authors use the Random Optimization Algorithm rather than back-propagation because it gives faster learning and a smaller mean squared error.

Ip and Wong [14] apply the Dempster-Shafer theory of evidence to the foreign exchange forecasting domain based on evidential reasoning. This theory provides a means for interpreting the partial truth or falsity of a hypothesis and for reasoning under uncertainties. Within the mathematical framework of the theory, evidence can be brought to bear upon a hypothesis in one of three ways: to confirm, to refuse…

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or to ignore. Different factors affect the exchange rate at different degrees at different times. Various competing hypotheses are assigned to the factors under consideration. Some factors reflect the economy of a country. The economy in turn provides evidence for the movement of its currency. Based on historical data that implicitly record trends and other external factors, the system is able to evolve. The accumulation of more data regarding time-varying parameters and past performance hypotheses is reflected in the accuracy of future hypotheses.

White and Racine [24] use ANN to provide inferences regarding whether a particular input or group of inputs “belong” in a particular model. The test of these inferences is based on estimated feed-forward neural network models and statistical re sampling techniques. The results suggest foreign exchange rates are predictable, but the nature of the predictive relation changes through time.

Ghoshray [10] used a fuzzy inferencing method on the fuzzy time series data to predict movement of foreign exchange rates. A fuzzy inference method uses one of the ingredients of chaos theory, which are the results of the previous iterations fed back repeatedly into the next one. He used fuzzy functions to express the dynamics of deterministic chaos. After certain steps any specific predicted value of the data vector could be obtained. He also found that fundamental analysis is useful in predicting long-term trends but of little use in predicting short-term movements of exchange rates. Even though technical analysis can be useful in predicting short-term period changes, there is a lack of consistent accuracy. The author has examined several forecasting techniques, considered the behaviour of time series data and advanced a fuzzy inference technique to predict future exchange rate fluctuations.

Iokibe, Murata and Koyama [13] use Takens’ embedding theorem and local fuzzy reconstruction technology to predict short-term foreign exchange rates. The Takens’ theory is that the vector X(t) = (y(t), y(t-τ), y(t-2τ), ……. y(t-(n-1)τ)) is generated from the observed time series y(t), where “τ” is a time delay. The embedded latest data vector is replaced with Z(T) = (y(T), y(T-τ), y(T-2τ), ……. y(T-(n-1)τ)). After one step is fetched, the data vector including this data is replaced with Z(T+1). The value of the time series data is predicted by the local fuzzy reconstruction method after “s” steps. This sequence is iterated up to the last data by setting dimensions of embedding (n=5) and a delay time of (τ=2) and the number of neighbouring data vectors (N=5) on the currency exchange rate data of different countries. The satisfactory results have proven this method suffers less on irregular phenomenon governed by contingencies of the financial market.

Muhammad and King [17] indicate fuzzy networks provide better general logic for modelling non-linear, multivariate and stochastic problems by using four layers; i.e., using fuzzy input, fuzzy rules, normalizing and defuzzifying sequences. This method not only improves the root mean square error (RMSE) but also gives a good track of the actual change in the foreign exchange market.

II. METHODOLOGY

One of the current challenges in time series forecasting approaches is in the area of financial time series. It is a function approximation problem. Pattern recognitions are performed on the monthly foreign currency exchange rate data to predict the future exchange rate. The future value is predicted by using time series analysis or regression techniques in this thesis. Regression involves the learning of the function that does this mapping. Regression assumes that the target data fits into some known type of function (e.g., linear or logistics) then discerns the best function that models the given data. An appropriate type of error analysis (MSE, for example) is used to determine which function is the most efficient.

We use option mining to recognize patterns within the data by adjusting the weights and biases so that the set of inputs generates the desired set of outputs.

A. Data description

We use the monthly time series of foreign currency exchange rate between Australian dollars with the currencies of other countries (e.g., U.S. dollars, Japanese yen, and Chinese yuan). The goal of this paper is to predict future FOREX rates. The data being used for training and testing is from 1969 to 1989 monthly foreign currency exchange rates. There are two types of basic input vectors. One is concurrent data and the other one is sequential data. Time series is sequential data. In this thesis the input data has two dimensions. One is year and the other is month. The output data has one dimension, which is the exchange rate.

B. Data pre processing

The utilized data has three columns, which are years, months and exchange rates. Thus the larger value input vector (e.g., year as compared to month) compares the month values and exchange rates value. This can lead to changes in the weights and biases that take a longer time for a much smaller input vector to overcome.

The regular rule for updating weighting is:

\[ \Delta W = (T - A) P' = E P' \quad (1) \]

Where W is weight. T is target. A is output. E is error. P is input.

As shown above, the larger an input vector P, the larger is its effect on the weight vector W. Thus if an input vector is much larger than other input vectors, the smaller input vectors must be presented many times to have an effect.

The solution is to normalize the data; that is, compress the data into a smaller arrangement. One of the functions for normalizing data is as follows:

\[ X n = (X - X \min) / (X \max - X \min) \quad (2) \]

This compresses the data into an arrangement between 0 and 1. It scales the inputs and targets so that their values can fall in the range [−1, 1]. For this project, the input data is years and months. The target data are currency exchange rates. We use the following MQL4 command to pre process (normalize) the input matrix P and target matrix T:
[Pn, minP, maxP, Tn, minT, maxT] = premm[P, T;]
Now the original input data P and target T are normalized to input Pn and target Tn such that all fall in the interval [-1, 1]. The vector minP and maxP are the minimum and maximum value of the original P. The vector minT and maxT are the minimum and maximum value of the original T. Next Pn and Tn are put into the network to train it. After the network has been trained, these vectors should be used to transform any future input applied to the network. Subsequently, the post processing, postmmx function, is used to convert the output to the same units as the original target.

C. Partitioning of the data
In this thesis 70% of the data will be used for training and 30% of the data will be used for testing.

D. Choosing transform functions
Each input vector X is weighted with an appropriate matrix W, which is the dot product of the matrix W with the input vector X. The bias b is summed with the weighted input and put into the transfer function f. The transfer function takes the output, which may have any value between plus and minus infinity, and compresses the output into the range between 0 and 1. The range depends on which transfer function is chosen. The output of the node is $Y_i = f_i(\sum W_{ij}x_j + b_i)$. An additional reason to use a transfer function is to prevent noisy inputs from impacting analysis. There are many suggested transfer functions, including threshold, sigmoid, symmetric and Gaussian. The MQL4 Toolbox [8] has many commonly used transfer functions, including hard-limit, purelin, log-sigmoid and tan-sigmoid.

E. The Performance EA
The Performance EA is based on the effect of the size and colour of the candle bodies. For additional confirmation, many traders use indicators, so to make life easier in this thesis defined two simple indicators: haOpen and haClose.

In MetaStock, choose Tools, Indicator Builder, and New to create these four new indicators:
Name: haClose
haClose:=(O+H+L+C)/4;
Name: haOpen
haopen:=(PREV+Ref(Fml("haClose"),-1))/2;

III. EXPERIMENTAL RESULT

Currency: EUR/JPY, GBP/JPY
Time frame: 5 min
Indicators: BB 14, 2, ADX 14, SSD 5, 3, 3, EMA 9, 20, 55, 120

This technique is used in combination with Bollinger Bands 14, 2, ADX 14, SSD 5, 3, 3 and EMA 9, 55, 120.

Buy/Sell signals:
Entry: after two hollow or two filled candles.
Leading indicator: SSD 5, 3, 3, crosses often 1-2 bars before
Confirmation: +DI/-DI-line-crossover.
+DI (green) and -DI (red) line (ADX 14) crosses sometimes 1-4 bars afterward entry point.

Price Momentum:
+DI stays on top of -DI — uptrend is in place.
-DI stays on top of +DI — downtrend is in place.

Strategic Forex Trading:
ADX +/- DI lines are used for spotting entry signals.
All +/- DI crossovers are disregarded while ADX remains below 20.

Once ADX peaks above 20 a buy signal occur when +DI (green) crosses upwards and above -DI (Red).
A sell signal will be the opposite: -DI would cross +DI downwards.

Exit Points:
– When Performance Evaluation Tool changes and/or Performance Evaluation Tool closes over the counterpart side of EMA 9 line.
– In all situation of +DI/-DI-line-crossovers (when trend is changing - two DI cross).
– Buy and exit situations are often signalize with SSD 5, 3, 3, crossing near 20 or 80 % line.

Role Reversal:
If after a newly created signal another opposite crossover happens within a short period of time, the original signal should be disregarded and position protected soon or closed.

Watch the indicator:
When ADX rises above 20 for the first time and then goes flat for some time, there is believed to be a new trend being born and the reason for ADX being currently flat is because market reacts to this new trend formation by making first initial correction. During this correction it is a good time to initiate new orders. Spent some time reviewing shorter time charts as well (one-minute-time-frame).

– When ADX is too low, don’t trade. (Often come along with indifferent candles)(C) (C) Compare the above/underneath illustrations: earmarked ABC or ABCDE.

Yet another reason
– ADX indicator is never traded alone, but rather in combination with other indicators and tools.
ADX indicator most of the time gives much later signals comparing to faster reacting moving averages crossover or...
Bollinger Bands - the methodology of using Volatility indicators

In any market there are periods of high volatility (high intensity) and low volatility (low intensity). Volatility indicators show the size and the magnitude of price fluctuations. These periods come in waves: low volatility is replaced by increasing volatility, while after a period of high volatility there comes a period of low volatility and so on. Volatility indicators measure the intensity of price fluctuations, providing an insight into the market activity level.

Low volatility suggests a very little interest in the price, but at the same time it reminds that the market is resting before a new large move. Low volatility periods are used to set up the breakout trades. For example, when the bands of the Bollinger bands indicator squeeze tight, Forex traders anticipate an explosive breakout way outside the bands limit.

A rule of thumb is: a change in volatility leads to a change in price. Another thing to remember about volatility is that while a low volatility can hold for an extended period of time, high volatility is not that durable and often disappears much sooner.

There are three different ways you can set up trades with Bollinger Bands: Range Trading, Breakout Trading and Tunnel Trading.

Range is the distance between support and resistance for current price action. It is the space between the top and bottom of recent activity.

Bollinger Bands are self-adjusting. When the market becomes more volatile, the Bollinger Bands expand or open up and more in opposite directions from each other. Whenever price enters a tight trading pattern, the bands respond by contracting or moving closer together. In a range bound market, the bands are usually parallel to each other.
IV. CONCLUSION

This paper uses MQL4 neural network software as a tool to test different kinds of algorithms and network structures to find the best model for the prediction of FOREX rates. To date we have found that a network model using the LM as the training algorithm and 1-3-1 as the network structure has the best performance for FOREX rate data.

V. FUTURE WORK

Picking the learning rate for a nonlinear network is a challenge. Unlike linear networks, there are no easy methods for picking a good learning rate for nonlinear multi-layer networks.

Networks are also sensitive to the number of neurons in their hidden layers. Too few neurons can lead to under-fitting, too many can contribute to over-fitting. One may want to reinitialize the network and retrain several times to guarantee that one has the best solution. One significant direction in which we would like to expand our work is to explore more properties of MQL4 neural network software, testing more parameters to increase the accuracy of the prediction, decrease the time consumed in the process and reduce memory usage. More dimensions and more complex data should be tested to explore the potential for data analysis in MQL4. Overall, using the right analytical tools and methods can decrease the chance of making incorrect decisions and increase the possibility of profitability in the area of foreign currency exchange rates.

REFERENCES


