Combining Empirical Mode Decomposition with Neural Networks for the Prediction of Exchange Rates

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Abstract: This paper proposes a neural network based model applied to empirical mode decomposition (EMD) filtered data for multi-step-ahead prediction of exchange rates. EMD is used to decompose the returns of exchange rates into intrinsic mode functions (IMFs) which are partially recomposed to produce a low-pass filtered time series. This series is used to train a neural network for multi-step-ahead prediction. Out-of-sample tests on EUR/USD and USD/JPY rates show superior performance compared to random walk and neural network models that do not employ EMD filtering. The novel approach of using EMD as a filtering technique in combination with neural networks consistently delivers higher returns on investment and demonstrates its utility in multi-step-ahead prediction.

1 INTRODUCTION

The prediction of foreign exchange rates presents several known challenges, the foremost being the wide variety of behaviours that are observable at many different time scales. The optimal choice of time scale and forecast horizon for profitable trading is a nontrivial matter, as the parameters at which the signal shows the most predictable and exploitable behaviour have to be found. A further challenge is introduced by the inherent nonlinearity in the relationship between past and future behaviour of foreign exchange rates (Hsieh 1989; Pavlidis et al. 2012; Nusair 2013) .

Empirical Mode decomposition (EMD) is a technique designed to decompose a signal into its intrinsic modes (Huang et al. 1996), and has seen wide usage in the area of financial analysis. What makes EMD attractive in financial analysis is that it is an empirically based technique that is *a posteriori* and adaptive, allowing the data to speak for itself. No *a priori* assumptions are required, as is the case with traditional time-frequency techniques such as Fourier or wavelet analyses. Time series analysis traditionally seeks for a suitable model to fit the data; this is complicated by the fact that the data is typically non-stationary, with non-linear relationships between past and future values and behaviour occurring simultaneously at different time scales. The time-frequency components obtained from EMD can simplify this task by allowing one to investigate the series for one intrinsic mode function (IMF) at a time and over time horizons that are optimal for the respective IMFs. While EMD is traditionally used to analyse the individual modes of a time series, usage of the technique as a filter has also been identified (Huang et al. 2003; Flandrin 2004). An advantage of EMD-filtering is that the data still retains its nonlinearity and non-stationarity, which is not the case when using conventional filtering techniques.

Artificial Neural Networks (ANN's) are a widely used machine learning technique that simulates the structure of a biological neural network. The structure of the neural network consists of nodes distributed across input, hidden and output layers, connected by weighted connections and activation functions (Laurene Fausett 1994). This structure gives neural networks the built-in property to identify nonlinear relationships between input and output variables, making it ideal for application to nonlinear domains such as financial prediction.

This paper proposes an ANN model applied to data filtered with a novel EMD-filtering technique for multi-step prediction of foreign exchange rates. The purpose of the prediction will be to maximize the returns of an investor by identifying the most exploitable sampling period and forecast horizon

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using empirical methods. The training and input data will be filtered to suit the forecast horizon with the goal of improving the signal to noise ratio for the appropriate time scale. The EMD-filtered ANN model will be tested on out of sample exchange rates, and will be compared with an ANN applied to unfiltered data and a random walk model in terms of accuracy of predictions and simulated returns on an investment. The proposed model will give insight into the ability of EMD-filters to improve exploitable prediction accuracy by attempting to increase the signal-to-noise ratio of the neural network's training data.

The rest of the paper is organized as follows: In Section 2 a survey of the literature on EMD-based machine learning is provided. Section 3 discusses the methodology of the proposed model. Section 4 describes the data, pre-processing, performance criteria and implementation of the proposed model. The experimental results are also given and discussed in Section 4. Section 5 concludes the paper.

2 LITERATURE SURVEY

Machine learning techniques have been widely used to forecast foreign exchange rates since the early 1990's. For an overview of applications of machine learning techniques to exchange rate prediction, Imam's survey article is recommended (Imam, 2012).

Our literature survey will focus on the use of EMD in combination with machine learning in the area of financial prediction. Huang et al. investigated the use of EMD for analysis of non-stationary financial time series (Huang et al., 2003). They found that EMD with the Hilbert transform offered better temporal and frequency resolutions than Wavelet or Fourier analysis. The utility of EMD as a filter to separate and extract variability on different time scales was also noted. Wang examined the predictive capability of an EMD-based Support Vector Regression (SVR) model on the Shanghai Securities Index. The EMD-based model performed significantly better than the SVR model on its own for both singe-step-ahead and multi-step-ahead predictions (W. Wang et al., 2009). Several studies focused on forecasting exchange rates using EMD-based SVR models (Fu 2010; C. Lin et al., 2012; Cheng and Wei 2014). For each case the EMD-based model proved to have superior forecasting accuracy compared to non-EMD-based or statistical models. An EMD-based neural network was designed in order to forecast financial crises using exchange rate data (Yu et al., 2010). The EMD-based model outperformed both statistical and neural network models in correctly identifying crises. Yang also used an EMD-based back propagation neural network model to forecast the daily NTD/USD rate, with the proposed model outperforming a random walk model for all performance evaluation criteria (Yang and H. Lin 2012). Two separate studies exist on the application of EMD and neural networks in order to forecast crude oil prices (Yu et al., 2008; Xiong et al., 2013). Yu et al. noted superior accuracy for one-step-ahead prediction, while Xiong found that the EMD model also proved to be more accurate for multi-step-ahead prediction.

3 METHODOLOGY

3.1 Empirical Mode Decomposition

EMD assumes that a signal is composed of a number of intrinsic mode oscillations with distinct frequency bands. These components, called Intrinsic Mode Functions (IMFs), superimpose upon each other in order to form the observable signal. An IMF is a signal that satisfies the following two conditions:

1) For the whole data set the difference in the number of extrema and zero crossings must be less than or equal to one.
2) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero.

The sifting procedure used to decompose a signal $x(t)$ into IMFs can be described in terms of the following steps:

1) Identify local extrema of $\mathrm{x(t)}$
2) Connect all local maxima using a cubic spline interpolate to obtain the upper envelope $\mathrm{x_{up}(t)}$ and connect the local minima using a cubic spline interpolate to obtain the lower envelope $\mathrm{x_{low}(t)}$
3) Obtain the mean envelope:
$$m(t) = \left(x_{up}(t) + x_{low}(t)\right)/2 \quad (1)$$
4) Extract the difference variable
$$d(t) = x(t) - m(t) \quad (2)$$
5) Check whether $d(t)$ fulfils the above mentioned IMF conditions. If the conditions are met then $d(t)$ is an IMF and $x(t)$ must be replaced with the residual:
$$r(t) = x(t) - d(t) \quad (3)$$
If the conditions are not met, replace $x(t)$ with dt and repeat from step 1.

6) Steps 1 through 5 are repeated until the residual meets the stopping condition, SC:

$$\sum_{t=1}^{T} \frac{(d_j(t) - d_{j+1}(t))^2}{d_j^2(t)} < SC \qquad (4)$$

where $d_j(t)$ is the j[th] iteration's sifting result.

The sifting procedure described above produces IMFs, each with a distinct frequency band. This allows one to view the EMD technique as a filter bank, where each IMF is the product of a band pass filter that matches an inherent mode present in the signal (Flandrin, 2004).

3.2 Artificial Neural Networks

This study will use a three layer feed-forward neural network, which consists of the input, hidden and output layers. The input layer receives historic filtered exchange rate data. The hidden layer consists of 10 nodes, and the output layer is a single node for the predicted returns of exchange rate. The network will be trained using the Levenberg-Marquardt back-propagation algorithm. This algorithms seeks to optimise performance based on mean square error, and is accepted as one of the fastest back-propagation training algorithms.

3.3 Proposed Model

The proposed EMD-filtered ANN model is employed in order to do multi-step-ahead prediction with the purpose of exploitable trading on exchange rates. The procedure is shown in Figure 1 and consists of the following steps:

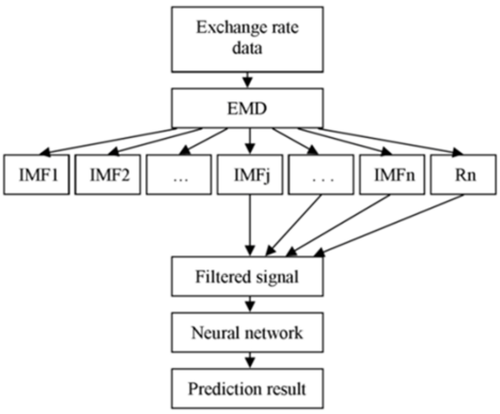

Figure 1: The proposed EMD-filtered ANN model.

Empirical Mode Decomposition of the data will decompose the time series into IMF's. A low-pass version of the signal is constructed by summation of IMF_j to IMF_n and the residue, where IMF_j is the IMF with an oscillation period with at least half the length of the forecast horizon. This filtered signal is used to train the feed-forward neural network using a Levenberg-Marquardt algorithm. The neural network input data used for the out-of-sample prediction will be filtered in similar fashion. The predicted values will be compared to the actual exchange rate values with the performance criteria of root-mean-square-error, directional symmetry, correlation and simulated returns generated by a simple trading strategy.

4 EXPERIMENTAL RESULTS

4.1 Data and Pre-Processing

In order to evaluate the forecasting performance of the proposed model, this study uses 30 minute sampled EUR/USD and USD/JPY closing rates from 1 January 2013 to 31 December 2013. All the rates are converted to normalised logarithmic returns, which is the fraction by which the current sample has changed compared to the previous sample, and is given by:

$$ret_i = \ln\left(\frac{rate_i}{rate_{i-1}}\right) \qquad (5)$$

The data is divided into 12 months. The previous month is used as the training set, with the subsequent month used as the out of sample testing set. This results in 11 training sets (January to November) and 11 testing sets (February to December), each with 1010 observations composed of the 5 most recent available data samples. The number of training observations was chosen to be at least ten times the number of weighted connections in the neural network, while the number of samples to include per training observation was determined using autocorrelation and mutual information analyses. An average bid-ask spread for the period was obtained from the Straighthold Investment Group's LiteForex server. The bid-ask spread is used in the calculation of the simulated returns of the predicted time series.

4.2 Performance Criteria

Following other research in the area of exchange rate prediction (Tay and Cao 2001; Lu et al., 2009; C. Lin et al., 2012), the following criteria are evaluated in order to measure the performance of the predictive model: root-mean-square-error (RMSE) and directional symmetry (DS). Two further criteria are used in order to measure the exploitable predictability of the models. The first is the percentage correlation between the actual and predicted normalised returns (Corr). The second is the simulated return percentage for the time period if a trading strategy is implemented based on the predictions. The simulation of the returns is conducted in the following way, with an initial balance of 100:

1) Check whether the next predicted sample is expected to deliver a positive or negative return.
2) If the return is positive, take a long position. If the return is negative, take a short position.
3) If the position in step 2 has changed from the previous position, take into consideration the bid-ask spread of the exchange rate.
4) If a long position has been taken in step 2, calculate the returns for that step using the actual returns and the current balance. If a short position has been taken, the entire balance is withdrawn from the security and is kept unchanged, except for the bid-ask-spread where applicable.
5) Repeat steps 1 through 5 with the updated balance for the entire predicted series.
6) Calculate the percentage change between the initial and final balance. This is the simulated return for the time period.

The simulated returns (Ret) will give an indication of the out-of-sample exploitability of the model at the chosen sample rate and forecast horizon. Finally, the t-statistics for the returns generated by the prediction model are calculated using a two sample t-test between the returns of the models and the returns of the random walk.

4.3 EMD Filter

The training and test input data must be filtered for the EMD-filtered ANN model. Firstly the normalised return time series is decomposed into IMF's using the EMD method described in Section 3.1. See Figure 2 for an example of a decomposed segment of the normalised EUR/USD returns.

The EMD filter works on the principle of recomposition of a subset of the IMFs. Each IMF can be seen as a band-passed component of the composite signal. For effective training of a neural network for multi-step-ahead prediction, it is necessary to design a Nyquist filter. This filter is a low-pass filter that cuts off at an oscillation period that is at least half the length of the forecast horizon. The recomposition of the remaining IMFs in a descending order will result in a low-passed filtered version of the original signal, and is illustrated in Figure 3.

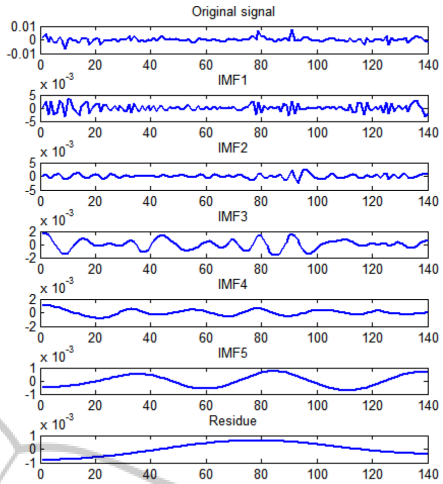

Figure 2: EMD results for an extract of the normalised EUR/USD returns.

4.4 Forecasting Results

The forecasting results of the proposed EMD-filtered ANN model are compared to a random walk and an unfiltered ANN model. The models are compared based on the performance criteria of the out of sample prediction of the EUR/USD and USD/JPY exchange rates. Table 1 shows the average monthly performance measurements that are calculated by comparing the actual and the predicted values of the EUR/USD exchange rate, while Table 2 shows the average monthly performance measurements of the USD/JPY exchange rate. The choice of forecast horizons stems from an analysis of the frequencies found consistently in the IMFs at the current sample rate.

4.5 Findings

After analysis of the experimental results, the findings are as follows:

- The EMD-filtered ANN model outperforms the ANN and the random walk models in terms of directional symmetry, correlation and simulated returns for both exchange rates and all forecast horizons.
- The USD/JPY exchange rate offers higher returns, which could indicate larger movements or decreased market efficiency.
- As the forecast horizon lengthens, some of the exploitable price movements are lost due to less frequent trading.
- The t-test at a significance level of 0.05 rejects the similarity in returns between the proposed EMD-filtered ANN model and the random walk model.

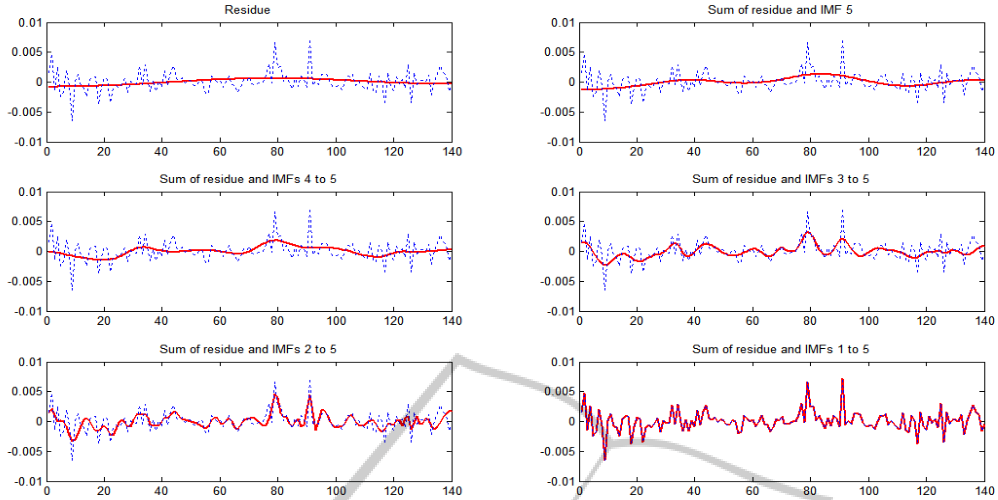

Figure 3: Recomposition of EUR/USD IMFs at different levels resulting in different low-pass filtered versions of the original signal.

Table 1: Average monthly exchange rate forecasting results of the EMD-filtered ANN, ANN and random walk models for the 30 minute EUR/USD exchange rate.

1.5 Hour forecast horizon					
Average maximum possible monthly returns(%)			9.8971		
Model	RMSE	DS(%)	Corr	Ret(%)	t-value
EMD-filter ANN	0.0012	63.93	0.3503	1.9046	6.3858
ANN	0.0013	56.28	-0.0174	-1.7120	2.9138
Random Walk	0.0014	40.40	-0.0044	-3.7652	0
4.5 Hour forecast horizon					
Average maximum possible monthly returns(%)			6.6964		
Model	RMSE	DS(%)	Corr	Ret(%)	t-value
EMD-filter ANN	0.0021	65.18	0.2611	1.3721	5.9875
ANN	0.0021	54.95	0.0417	-0.6215	1.8941
Random Walk	0.0022	45.29	-0.0376	-1.8045	0
11 Hour forecast horizon					
Average maximum possible monthly returns(%)			4.9623		
Model	RMSE	DS(%)	Corr	Ret(%)	t-value
EMD-filter ANN	0.0032	66.87	0.3618	1.5141	3.0390
ANN	0.0034	48.48	-0.0913	-0.4948	-0.7218
Random Walk	0.0033	49.29	-0.0129	-0.0403	0
20 Hour forecast horizon					
Average maximum possible monthly returns(%)			3.9599		
Model	RMSE	DS(%)	Corr	Ret(%)	t-value
EMD-filter ANN	0.0045	65.53	0.4852	1.5795	2.3505
ANN	0.0044	54.55	-0.0518	-0.2013	-0.2831
Random Walk	0.0042	53.03	0.0504	0.0014	0

Table 2: Average monthly exchange rate forecasting results of the EMD-filtered ANN, ANN and random walk models for the 30 minute USD/JPY exchange rate.

1.5 Hour forecast horizon					
Average maximum possible monthly returns(%)			20.0362		
Model	RMSE	DS(%)	Corr	Ret(%)	t-value
EMD-filter ANN	0.0017	64.52	0.3647	5.8295	6.7179
ANN	0.0018	52.75	0.0261	-2.2571	0.7851
Random Walk	0.0021	40.42	-0.0180	-3.004	0
4.5 Hour forecast horizon					
Average maximum possible monthly returns(%)			12.4100		
Model	RMSE	DS(%)	Corr	Ret(%)	t-value
EMD-filter ANN	0.0029	62.66	0.38110	3.7767	4.6926
ANN	0.0031	51.54	0.0304	0.0199	1.0428
Random Walk	0.0032	45.70	-0.0090	-1.0180	0
11 Hour forecast horizon					
Average maximum possible monthly returns(%)			8.5538		
Model	RMSE	DS(%)	Corr	Ret(%)	t-value
EMD-filter ANN	0.0044	64.44	0.4526	3.5785	4.1577
ANN	0.0048	49.4949	-0.0334	1.2897	0.9576
Random Walk	0.0047	42.02	0.0107	0.3441	0
20 Hour forecast horizon					
Average maximum possible monthly returns(%)			6.9709		
Model	RMSE	DS(%)	Corr	Ret(%)	t-value
EMD-filter ANN	0.0078	68.18	0.4193	3.4000	2.3069
ANN	0.0068	51.5152	0.0133	0.1846	-0.6564
Random Walk	0.0033	50.00	0.0566	0.6990	0

5 CONCLUSIONS

Forecasting non-linear financial time series has received increased attention in recent years. This paper proposed a novel EMD-filter in combination with a neural network in order to forecast exchange rates with the purpose of profitable trading. The proposed model is compared to an unfiltered neural network and a random walk model for out-of-sample prediction of the EUR/USD and USD/JPY rates of 2013.

The proposed EMD-filtered neural network was the best performing model based on the criteria of directional symmetry, correlation and simulated returns. This can be attributed to the EMD-filter's ability to increase the signal-to-noise ratio for the applicable forecast horizon. The results are in accordance with previous studies on EMD-based prediction models where the use of EMD has improved the prediction accuracy.

The two sample t-test rejects the similarity between the returns generated by the proposed EMD-filtered ANN model and the random walk model at a significance level of 99% in all cases except for 20 hour prediction horizons, where the significance level if 95%. This is an indication that the proposed model can consistently deliver higher returns than a random walk at all the forecast horizons for both exchange rates.

In conclusion, the out-of-sample test results reveal that EMD-filtered ANN forecasting can be an effective tool for investors in predicting exchange rates.

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