Foreign Currency Exchange Rate Prediction using Neuro-Fuzzy Systems

Yoke Leng Yong[1,*], Yunli Lee[1,*], Xiaowei Gu[2], Plamen P Angelov[2,3], David Chek Ling Ngo[1,4], and Elnaz Shafipour[2]
[1]Sunway University, Malaysia
[2] School of Computing and Communications, Lancaster University, Lancaster, UK
[3] Honorary Professor, Technical University, Sofia, Bulgaria
[4] Wawasan Open University, Malaysia
14071856@imail.sunway.edu.my, yunlil@sunway.edu.my, x.gu3@lancaster.ac.uk, p.angelov@lancaster.ac.uk, dclngo@ieee.org, e.shafipouryourdshahi@lancaster.ac.uk

Abstract

The complex nature of the foreign exchange (FOREX) market along with the increased interest in the currency exchange market has prompted extensive research from various academic disciples in aiding traders in their in-depth analysis and decision making processes. An approach incorporating the use of historical data along with computational intelligence for analysis and forecasting is proposed in this paper. Firstly, the Gaussian Mixture Model method is applied for the purpose of data partitioning on historical observations. Then, the antecedent part of the neuro-fuzzy system of AnYa type is initialized by the partitioning result and the consequent part is trained using the fuzzily weighted RLS algorithm based on the same data. Numerical examples based on the real currency exchange data demonstrated that the proposed approach trained with historical data is able to produce optimizing results on forecasting the future foreign exchange rates for a very long period, and also show the potential of the proposed approach in real applications.

1 Introduction

The foreign exchange (FOREX) market is often perceived to be extremely complex and volatile in nature. As the FOREX market is constantly affected by various external factors that must be taken into consideration, it is often not easy to obtain reliable currency exchange price forecasting. In addition, there are also elements of subjectivity involved in analyzing and interpreting the results

[*] Corresponding author

obtained. Although advances in FOREX market research provided additional insights for the traders, the analysis and forecasting methods used are still subjected to heuristics and prior experience. Hence, numerous analysis methods have been introduced to aid traders in gaining the upper-hand by making an informed decision while trading. An influx of traders from different trading background along with the high daily trading volume within the FOREX market has contributed to the paradigm shift within the trading community. Therefore, extensive research incorporating methods from various academic disciplines such as computational finance and econometrics have been undertaken by various researchers to obtain accurate FOREX forecasting.

Currently, the widely-used analysis methods can be divided into three major categories, namely Fundamental Analysis, Sentiment Analysis and Technical Analysis. However, previous surveys reveal that most of the traders are still subscribed to some form of technical analysis methods when making trading decisions (Neely & Weller, 2011; Schulmeister, 2008).

Compared to other analysis methods, technical analysis emphasizes heavily on the use of FOREX historical exchange rate for analysis and forecasting. This is partly due to two of the most important assumptions behind the core concept of technical analysis, 1) the FOREX currency exchange prices often fluctuate in trends, and 2) the trends developed tend to repeat over time. In fact, various studies have been conducted on prediction of FOREX rates using machine learning techniques such as Artificial Neural Network (ANN) (Yao & Tan, 2000; Emam, 2008; Zafeiriou & Kalles, 2013), Genetic Algorithm (GA) (Slany, 2009; Theofilatos, Likothanassis, & Karathanasopoulos, 2012), and Neuro Fuzzy Computing geared towards ANFIS implementation (Fahimifard, Homayounifar, Sabouhi, & Moghaddamnia, 2009; Bagheri, Mohammadi Peyhani, & Akbari, 2014).

In this paper, a new approach named Gaussian Mixture Model Initialized Neuro-Fuzzy (GMMINF) is proposed for foreign currency exchange rate prediction. The proposed approach involves Gaussian Mixture Model (GMM) method for historical foreign exchange data partitioning/clustering, and then, initializes a neuro-fuzzy system of AnYa type (Angelov & Yager, 2012) with the partitioning results obtained by the GMM method and further trains the consequent parameters of the neuro-fuzzy system using the same historical data via fuzzily weighted RLS algorithm (Angelov & Filev, 2004). Numerical examples demonstrate that after the offline training process, the proposed GMMINF predictor is able to provide accurate/stable prediction results on the future foreign currency exchange rate after offline training with the historical exchange rate.

The main procedure of the proposed approach is provided in Section 2. Section 3 provides the relevant information on the implementation of the proposed algorithm such as the dataset used, benchmarking methods, comparative algorithms as well as the results obtained. Lastly, Section 4 concludes the study of the proposed implementation in forecasting the FOREX market.

2 GAUSSIAN MIXTURE MODEL INITIALIZED NEURO-FUZZY PREDICTOR

In this section, the proposed Gaussian Mixture Model Initialized Neuro-Fuzzy (GMMINF) predictor is described. The offline training process of proposed approach consists of two stages. In the first stage, the Gaussian mixture model (GMM) clustering algorithm is used to group the historical data into several clusters and build up the presumed Gaussian mixture model. In the second stage, the peaks of the Gaussian distributions are used as the antecedent part of the neuro-fuzzy system, and the fuzzily weighted RLS method (Angelov & Filev, 2004) is used to identify the consequent parts in an iterative, offline manner. After the training process, the GMMINF predictor can conduct prediction in real time on the validation data.

First of all, let us denote the collection of the historical FOREX data samples serving as the inputs of the proposed predictor as $\{\boldsymbol{x}\}_K = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, ..., \boldsymbol{x}_K\}$ and the corresponding desired outputs as $\{y\}_K = \{y_1, y_2, y_3, ..., y_K\}$, where K denotes the current time instance; $\boldsymbol{x}_i = \left[x_{i,1}, x_{i,2}, ..., x_{i,M}\right]^T$ denotes the data sample observed as the i^{th} time instance, $i = 1, 2, ..., K$; M is the dimensionality of the data space. The two-stage training process of the proposed GMMINF predictor is firstly described as follows.

2.1 Training Stage 1: Clustering with GMM

In this stage, we identify the main pattern of the collected historical FOREX data using the GMM method. The GMM method is a widely-used clustering algorithm that can group the data into clusters with the centers as the peaks of the Gaussian mixture distribution presumed by the GMM approach. The distribution of each observation is specified by a probability density function through a finite mixture model of G components as represented in Equation (1). This can be easily achieved by using the implementation of GMM for clustering available in R software for statistical computing (R Core Team, n.d.). The function “Mclust()” from the package “mclust” (Scrucca, Fop, Murphy, & Raftery, 2016) provides the model based clustering required with the Gaussian distribution.

$$f\left(\boldsymbol{x}_i \mid \boldsymbol{\varphi}\right) = \sum_{k=1}^{G} \pi_k f_k\left(\boldsymbol{x}_i ; \boldsymbol{\theta}_k\right) \tag{1}$$

where $\boldsymbol{\varphi}$ are the parameters of the mixture model, G is the number of mixture components, ($\pi_1, \pi_2, ..., \pi_G$) are the mixing weight probabilities and $f_k\left(\boldsymbol{x}_i ; \boldsymbol{\theta}_k\right)$ is the k^{th} component density for observation $\boldsymbol{x}_i$ with parameter vector $\boldsymbol{\theta}_k$. Detailed discussion of the implementation is available in the R official documentation (Scrucca, Fop, Murphy, & Raftery, 2016).

The parameters of the Mclust function are the set of historical FOREX data which consists of daily open, high, low and close prices, the number of mixture components (G) is set to $1:30$, and Gaussian Model is set to VII, which represents a spherical unconstrained model.

By using the GMM method, a number of clusters are identified from $\{\boldsymbol{x}\}_K$ with the corresponding centers, average scale products and supports denoted by $\boldsymbol{\mu}_i$, X_i and S_i ($i = 1, 2, ..., N$, N is the number of clusters), respectively, and the proposed approach can enter the second stage.

2.2 Training Stage 2: Neuro-Fuzzy System Identification

In this stage, firstly, the neuro-fuzzy system of AnYa type (Angelov & Yager, 2012) is initialized by the centers of the clusters, which correspond to the peaks of the Gaussian mixture model in the following form:

$$Rule_i: \quad IF\ \left(\boldsymbol{x} \sim \boldsymbol{\mu}_i\right) \quad THEN\ \left(y_i = \bar{\boldsymbol{x}}^T \boldsymbol{a}_i\right) \tag{2}$$

where $\bar{\boldsymbol{x}}^T = \left[1, \boldsymbol{x}^T\right]$; $\boldsymbol{a}_i = \left[a_{i,0}, a_{i,1}, ..., a_{i,M}\right]^T$, which is the consequent parameter vector of the i^{th} fuzzy rule.

The consequent parameters $\boldsymbol{a}_i$ and the covariance matrixes $\mathbf{C}_i$ ($i = 1, 2, ..., N$) of neuro-fuzzy system are firstly initialized as:

$$\boldsymbol{a}_i^{(0)} = \mathbf{0}_{(M+1)\times 1}; \quad \mathbf{C}_i^{(0)} = \mathbf{I}_{(M+1)\times(M+1)} \tag{3}$$

where $\mathbf{0}_{(M+1)\times 1}$ is a $(M+1)\times 1$ dimensional zero vector; $\mathbf{0}_{(M+1)\times 1} = \left[\overbrace{0,0,...,0}^{M+1}\right]^T$; $\mathbf{I}_{(M+1)\times(M+1)}$ is a $(M+1)\times(M+1)$ dimensional identity matrix.

Then, the fuzzily weighted RLS method is used to update the consequent parameter $\boldsymbol{a}_i^{(l)}$ ($l=1$, l is the index of the current consequent parameter-updating loop) of each rule iteratively with $\boldsymbol{x}_k$ and y_k from $k=1$ to $k=K$ (Angelov & Filev, 2004):

$$\mathbf{C}_i^{(l)} \leftarrow \mathbf{C}_i^{(l)} - \frac{\lambda_{k,i}\mathbf{C}_i^{(l)}\overline{\mathbf{x}}_k\overline{\mathbf{x}}_k^T\mathbf{C}_i^{(l)}}{1+\lambda_{k,i}\overline{\mathbf{x}}_k\mathbf{C}_i^{(l)}\overline{\mathbf{x}}_k^T} \tag{4}$$

$$\boldsymbol{a}_i^{(l)} \leftarrow \boldsymbol{a}_i^{(l)} + \lambda_{k,i}\mathbf{C}_i^{(l)}\overline{\mathbf{x}}_k\left(y_k - \overline{\mathbf{x}}_k^T\boldsymbol{a}_i^{(l)}\right) \tag{5}$$

where $\lambda_{k,i}$ is the activation level of $\boldsymbol{x}_k$ to the i^{th} fuzzy rule expressed as follows (Angelov, Gu, & Principe, 2017b):

$$\lambda_{k,i} = D_i\left(\boldsymbol{x}_k\right) \Big/ \sum_{j=1}^{N} D_j\left(\boldsymbol{x}_k\right) \tag{6}$$

and $D_{k,j}\left(\boldsymbol{x}_k\right)$ is the local density of $\boldsymbol{x}_k$ at the j^{th} cluster (Angelov, Gu, & Principe, 2017a):

$$D_j\left(\boldsymbol{x}_k\right) = \frac{1}{1+\dfrac{S_j^2\left\|\boldsymbol{x}_k-\boldsymbol{\mu}_j\right\|^2}{\left(S_j+1\right)\left(S_jX_j+\left\|\boldsymbol{x}_k\right\|^2\right)-\left\|\boldsymbol{x}_k+S_j\boldsymbol{\mu}_j\right\|^2}} \tag{7}$$

After each consequent parameter-updating loop is finished, the root mean-square error (RMSE) of the estimated outputs of the fuzzy logic predictor is calculated as follows:

$$\mathrm{E}^{(l)} = \sqrt{\frac{\sum_{k=1}^{K}\left(y_k-\hat{y}_k\right)}{K}} = \sqrt{\frac{\sum_{k=1}^{K}\left(y_k-\sum_{j=1}^{N}\lambda_{k,j}\overline{\boldsymbol{x}}_k^T\boldsymbol{a}_j^{(l)}\right)}{K}} \tag{8}$$

where $\hat{y}_k$ is the output of the predictor and there is $\hat{y}_k = \sum_{j=1}^{N}\lambda_{k,j}\overline{\boldsymbol{x}}_k^T\boldsymbol{a}_j^{(l)}$.

If $\mathrm{E}^{(l-1)} - \mathrm{E}^{(l)} \le \gamma_o$, the consequent parameters of the neuro-fuzzy system have converged to the locally optimal solutions and the loop stops ($\boldsymbol{a}_i \leftarrow \boldsymbol{a}_i^{(l)}$, $i=1,2,...,N$). Otherwise, another consequent parameter-updating loop begins ($l \leftarrow l+1$). In this paper, we use $\gamma_o = 10^{-6}$.

Once the consequent parameters have been identified, the GMMINF predictor is able to conduct real time prediction on the new data. The validation process is described in the following subsection.

2.3 Validation Stage

During the validation stage, for each newly observed data sample, $\boldsymbol{x}$, the output of the GMMINF predictor is calculated as follows:

$$\hat{y} = \sum_{j=1}^{N} \frac{D_i\left(\boldsymbol{x}\right)}{\sum_{k=1}^{N} D_k\left(\boldsymbol{x}\right)} \overline{\boldsymbol{x}}^T \boldsymbol{a}_j \tag{9}$$

3 PROPOSED IMPLEMENTATION

3.1 Dataset Description

Despite the wide variety of currency pair traded around the world, we only focus on some of the most traded currencies pairs. In this paper, we consider AUD/USD, EUR/USD, and GBP/USD, which are also known as the major currency pairs. The historical currency exchange price of the three major currency pairs from the 2 January 2002 – 30 December 2016 are obtained from HistData.com (HistData, n.d.). Figure 1 below depicts the daily EUR/USD data used in obtaining the results.

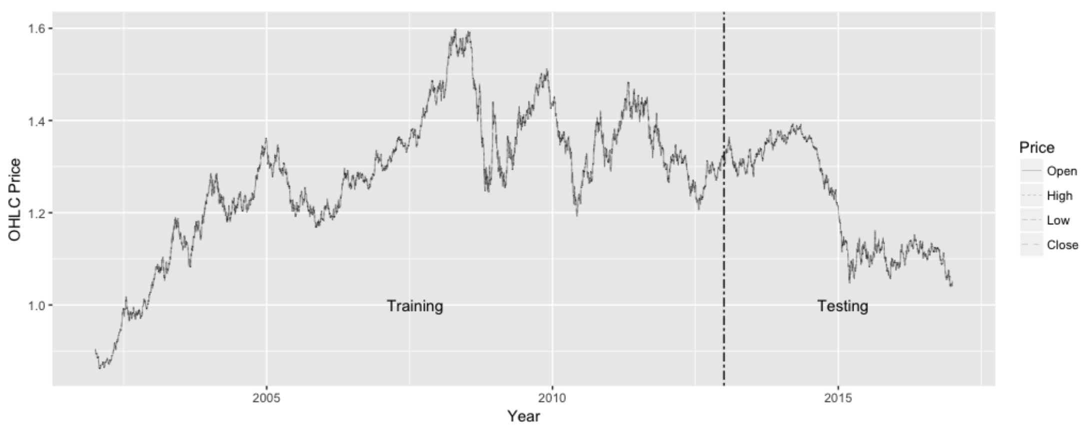

Figure 1: EUR/USD Dataset (2 January 2002 – 30 December 2016)

The full dataset consists of the following information:

1) Date;
2) Time;
3) Open Price;
4) High Price;
5) Low Price;
6) Close Price.

The data collected is further divided into training and testing dataset with a 70:30 percent ratio for training and testing purposes. Only the four attributes, Open, High, Low and Close Prices, are used in the experiments. We use the Open, High, Low and Close Prices of the current step to predict the Close Price one-step ahead.

3.2 Benchmarking Criteria

To examine the performance of the proposed algorithm against the testing data (ground truth), we need to select some suitable performance measures for the proposed implementation. Although plethora of benchmarking criteria are available for use, there are certain benchmarking metrics utilized more often by researchers. In this paper, Root Mean Squared error (RMSE), Mean Absolute Percentage Error (MAPE), and Non-Dimensional Error Index (NDEI) as indicated in Equations (8), (10) - (11) are chosen to evaluate the forecasting performance due to their popularity among academic researchers.

$$NDEI = RMSE/\sigma(Y) \tag{10}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left(\frac{\left|Y_i - \hat{Y}_i\right|}{Y_i}\right) \tag{11}$$

where Y is the actual test data, $\hat{Y}$ is the predicted data and *n* is the number of element within the test dataset.

3.3 Comparative Algorithms

The autonomous learning multi-model (ALMMo) predictor is a newly introduced autonomous learning neuro-fuzzy system for streaming data (Angelov, Gu, & Principe, 2017b), which can self-organize and self-evolve its multi-model architecture in a non-parametric, non-iterative, online way. It has been demonstrated that the ALMMo neuro-fuzzy system can provide highly accurate performance in the high frequency trading problems. Therefore, in this paper, we also involve the ALMMo neuro-fuzzy system for prediction (Angelov, Gu, & Principe, 2017b).

The detailed learning process of the ALMMo neuro-fuzzy system has been given in (Angelov, Gu, & Principe, 2017b). The source codes (in both the Matlab and Python versions) of the ALMMo neuro-fuzzy system are downloadable from: http://empiricaldataanalytics.org/downloads.html.

In this paper, we use two versions of the ALMMo neuro-fuzzy system for comparison, namely, ALMMo_Evolving and ALMMo_Offline. The ALMMo_Evolving will continue to self-evolve its system structure and parameters based on the validation data after the online sample-by-sample training process. The ALMMo_Offline will stop learning during the validation stage after the online training process.

3.4 Results

The clustering results obtained by the GMM method (the implementation is discussed in Section 2) using the training datasets are as follows:

EUR-USD: 18 clusters
AUD-USD: 21 clusters
GBP-USD: 18 clusters

The clustering result of EUR/USD is shown in Figure 2 with different colors representing distinctive clusters. Further inspection on the test dataset reveals that the initial price recorded is the same for both the Low and Close Prices. Therefore, both the Low and Close Prices could be used as ground truth in obtaining the three (3) performance benchmark selected. Table 1 gives the forecasting results on the Close Price, and forecasting results on the Low Price are listed in Table 2.

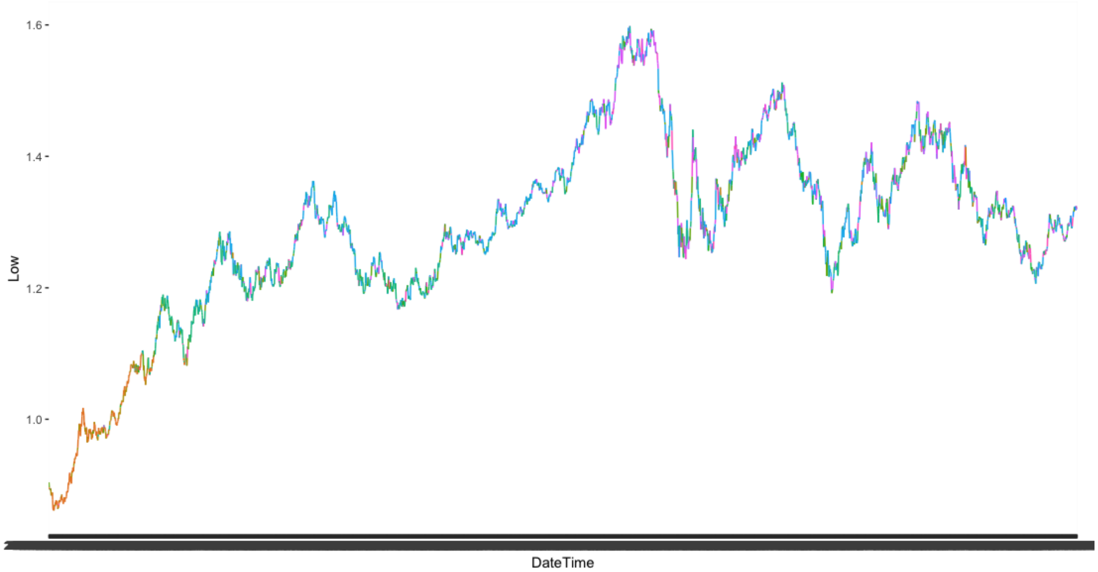

Figure 2: EUR/USD GMM Clustering

Table 1: Forecast results benchmarked against Close Price

	Algorithm	Rule# [a]	RMSE	NDEI	MAPE
EUR/USD	GMMINF	18	0.0060	0.0520	0.3573
	ALMMo_Evolving	46	0.0060	0.0521	0.3579
	ALMMo_Offline	51	0.0061	0.0527	0.3654
AUD/USD	GMMINF	21	0.0050	0.0480	0.4463
	ALMMo_Evolving	55	0.0050	0.0480	0.4463
	ALMMo_Offline	60	0.0051	0.0489	0.4602
GBP/USD	GMMINF	18	0.0078	0.0654	0.3481
	ALMMo_Evolving	64	0.0078	0.0653	0.3471
	ALMMo_Offline	43	0.0079	0.0662	0.3563

[a] Number of fuzzy rules after the training.

The forecasting results reveal that the best predictions are provided by the ALMMo_Evolving predictor and GMMINF predictor followed by the ALMMo_Offline predictor. Although the results obtained by the ALMMo_Evolving and the GMMINF predictors are extremely close, the GMMNF predictor performs slightly better when benchmarked against both the Close and Low Prices for the

EUR/USD currency pair. On the other hand, the ALMMo_Evolving algorithm delivers a better result when benchmarked against the Low Price for AUD/USD and GBP/USD. The ALMMo_Evolving algorithm follows a similar pattern and performs better when benchmarked against the Close Price for GBP/USD. Therefore, overall optimistic results prove that the combination of GMM data space partitioning and ALMMo neuro-fuzzy forecasting system have the potential to be explored further in forecasting FOREX rates.

We also have to admit that the foreign currency exchange rates are actually much smoother and more stable compared with the stock trading prices/high frequency trading problems. As a result, the proposed GMMINF predictor is able to provide very good prediction results after the offline training without any modification on the model itself. The proposed predictor requires a full retraining if the pattern of the foreign exchange rates change dramatically in the future. In contrast, the ALMMo predictor is able to self-evolve all the time in both training and validation stages. Therefore, as future work, we will seek for new solutions to update the system structure and parameters of the proposed GMMINF predictor in real time.

Table 2: Forecast results benchmarked against Low Price

	Algorithm	Rule#	RMSE	NDEI	MAPE
EUR/USD	GMMINF	18	0.0060	0.0521	0.3585
	ALMMo_Evolving	46	0.0060	0.0522	0.3590
	ALMMo_Offline	51	0.0061	0.0528	0.3666
AUD/USD	GMMINF	21	0.0050	0.0480	0.4466
	ALMMo_Evolving	55	0.0050	0.0480	0.4464
	ALMMo_Offline	60	0.0051	0.0489	0.4601
GBP/USD	GMMINF	18	0.0078	0.0655	0.3485
	ALMMo_Evolving	64	0.0078	0.0654	0.3472
	ALMMo_Offline	43	0.0080	0.0664	0.3567

4 Conclusion

In this paper, we proposed a new approach named Gaussian Mixture Model Initialized Neuro-Fuzzy (GMMINF) for foreign currency exchange rate prediction. The experimental forecast results using GMMINF predictor for the main three currencies benchmarked against Close and Low prices are promising and exhibit the potential of the proposed approach in real applications. As future work, we will apply the proposed approach to more different problems and further investigate its performance. The online updating mechanism will be further investigated as well.

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