Bachelor of Science Dissertation

Intraday FX Spot Rates Prediction Using Deep Learning and Other Machine Learning Techniques

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Abstract

Foreign exchange market is the largest financial market and has been a research subject of both researchers and practitioners for a long time. One of the key objective is to predict currency exchange rates. Machine learning algorithms such as artificial neural network and support vector machine has been heavily applied on this field. However, as the rising star in artificial intelligence, deep learning has rarely been used on foreign exchange market before. Hence, this study focuses on building deep learning model to predict hourly exchange rates. A benchmark model, used ensemble empirical mode decomposition, multivariate adaptive regression spline, and support vector regression, was built to compare with deep learning model. It is also insightful to see if deep learning could prove its superiority over other state-of-art algorithms in foreign exchange market like its application in computer vision and image recognition. The result showed that deep learning performed better than the benchmark model as well as the basic time series models, especially during highly volatile or rapidly price-changing periods.

Subject Descriptions:

- Data Analytics
- Data Mining
- Machine Learning

Keywords:

Machine learning, deep learning, artificial intelligence, time series analysis, foreign exchange, prediction, trading strategy

Implementation Software and Hardware:

R, RStudio

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Song Haoze

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Introduction

This paper serves to fulfil the bachelor degree requirement of Business Analytics for Song Haoze. The project is initiated and proposed by Dymon Asia Capital (the frim), a multibillion alternative investment management firm that ranked as top 10 best performing global hedge fund in both 2011 and 2014 (*https://www.dymonasia.com/about/firm-history/*). The firm focuses on Asian Markets and specializes in Macro trading. The project serves to help the firm carry out research and analysis in Artificial Intelligence (AI) and its application in the foreign exchange market. More specifically, this project analyses the capability FX spot rates prediction using various complex machine learning models, especially deep learning.

The rest of the paper is organized as follows. In section 1, the background of foreign exchange market is presented as well as motivation of this project. Section 2 includes past papers that focused on foreign exchange market prediction with machine learning algorithms. Other important papers with high relevance to this project are also included in this section. Section 3 describes the different kinds of variables and corresponding datasets used for this project. Model training and testing was conducted and included in section 4. The last section is the conclusion.

Background and Motivation

Foreign exchange market, also known as FX market, is the most liquid and economically important financial market in the world. According to the Bank for International Settlements, daily trading in FX averaged $5.1 trillion in April 2016 (*http://www.bis.org/publ/rpfx16.htm*). Though down from $5.4 trillion in April 2013, it remains the largest market in terms of volume of trading – approximately 30 times larger than the New York Stock Exchange. FX is traditionally used by central banks, commercial banks, commercial companies, investment management firms, and hedge funds for currency trading. However, by the advancement of technology and the development of electronic trading infrastructures, the market has become available for small retailers.

In FX market, trades are automatically involved in the simultaneous purchase of one currency and sale of another currency. Currency pairs are financial instruments to facilitate trading and make trades easier to recognize. If one longs a currency pair, he buys the base currency – first listed currency, and implicitly sells the quote currency – second listed currency. Conversely, when one shorts a currency pair, he sells the base currency and buys the quote currency. While there are as many currency pairs in the world, the majors are the most traded that include Euro to US Dollar (EUR/USD), US Dollar to Japanese Yen (USD/JPY), British Pound to US Dollar (GBP/USD), Australian Dollar to US Dollar (AUD/USD), US Dollar to Canadian Dollar (USD/CAD), and US Dollar to Swiss Franc (USD/CHF).

FX facilitates international trade and global trading. It is vital to support exports and imports, which are necessary to gain access to resources also to create additional demand for goods and services. Lack of capability to trade in different currencies would limit the outlook of companies and deteriorate global monetary growth. FX is also an asset class to trade for investors. Individuals or institutions trade currencies to create alpha. Due to the high achievable leverage in FX market, investors can significantly boost returns that can be provided on an investment. The FX market is therefore very important for international economy and finance.

Given its importance, FX has received much attention in the academic and industrial research. However, the determination and prediction of FX rates has remained an enigma due to its complexity and volatility. Many correlated economic, political, and even psychological factors can affect FX rates. These factors interact in a highly convoluted fashion. Researchers and practitioners have devoted much effort to analysing the causality of different factors and to developing specific models to improve FX rates prediction accuracy. In general, there are typically three types of techniques for prediction: parametric models, non-parametric models, and AI technologies. Parametric model used to be a popular technique in the past, which includes autoregressive random variance (ARV) model (So *et al*., 1999), autoregressive conditional heteroscedasticity (ARCH) (Hsieh, 1989), autoregressive integrated moving average (ARIMA) model (Cheung, 1993), general autoregressive conditional heteroscedasticity (GARCH) (Bollerslev, 1990), chaotic dynamic (Peel & Yadav, 1995), and self-exciting threshold autoregressive models (Chappell *et al*., 1996). While these models may be good for a particular situation, they perform poorly for other applications. Each model pre-specifies a form and such particular specification will not be general enough to capture all the nonlinearities, which restricts the usefulness of these parametric models. Besides parametric models, some non-parametric models have been proposed to predict FX rates as well (Diebold & Nasan, 1990; Meese & Rose, 1991; Mizrach, 1992). However, non-parametric methods investigated in these studies are still unable to improve upon a simple random walk model in testing data.

There has been growing interest in the adoption of the state-of-the-art AI technologies to solve the problem. The prevailing stream of these advanced techniques focuses on machine learning, such as regression and neural networks. Among numerous machine learning algorithms, deep learning has been the focus of researchers lately due to the incessant breakthrough of computational power of personal computers. It is a powerful paradigm that allows large-scale task-driven feature learning from big data. The major fields of application include computer vision, automatic speech recognition, natural language processing, audio recognition, and bioinformatics where deep learning techniques have been manifested to produce a better result than that of traditional machine learning techniques. However, deep learning has received less attention within financial markets, especially FX market. To the best of the author's knowledge, few research papers have focused on deep learning in financial markets, with only a handful of them focusing on FX market.

The motivation for this project is to determine if deep learning models could outperform benchmark results generated by machine learning techniques that were shown to perform well in the FX market. The benchmark model for this project was proposed by Plakandaras *et al.* (2015), which comprises ensemble empirical mode decomposition (EEMD), multivariate adaptive regression spline (MARS), and support vector regression (SVR). Besides, traditional parametric models such as ARIMA and GARCH are also included.

This project focuses on hourly FX rates prediction as it is more beneficial in practical to assist traders' decision making. Due to the high volatility of the FX market, FX rates could fluctuate quite largely and rapidly, sometimes even within seconds. However, too short time difference would not be enough to run complex models on large datasets. Hence hourly data is deemed suitable for this research project as well as for practical use by the firm.

Literature Review

For the study of financial asset prediction, the first question to be answered is whether it is possible to forecast the behaviour of an economic variable. According to the efficient market hypothesis (EMH) introduced by Fama (1965), financial asset prices follow random walk pattern and hence renders the movement unpredictable. However, a vast literate has shown to disprove the EMH with several works rejecting it specifically for intraday FX data. For instance, Baviera *et al.* (2000) rejected the random walk hypothesis for high frequency FX returns. Baviera *et al.* (2002) found anti-persistent Markov behaviour of log-price fluctuations in high frequency FX rates, which in principle allows the possibility of a statistical forecast. Shmilovici *et al.* (2009) found that intraday FX rates are predictable above the random guess. These empirical evidences proved that certain predictability of FX rates exists and encouraged researchers to improve prediction accuracies.

Machine learning has been a major stream of techniques that constantly shown to produce promising results. ANN is heavily used for prediction in FX market. It is revealed by Kuan and Liu (1995) that ANN could be useful to predict FX rates after comparing the performance of multilayer perceptron and recurrent neural networks. NN was further shown by Bellgard and Goldschmidt (1999) to better exploit the nonlinear patterns in AUD/USD rates than traditional techniques. Dunis and Williams (2002) compared NN with other traditional parametric models and a logit model on the EUR/USD and reported the superiority of NN-based models over the others. Kamruzzaman and Sarker (2003) investigated three ANN models for the AUD/USD rate prediction with moving average indicators and concluded that ANN models outperformed the ARIMA model across different performance metrics. Fulcher *et al.* (2006) applied higher order NN in predicting the AUD/USD rate which reached 90% accuracy. Panda and Narasimhan (2007) used a single hidden layer feedforward NN to produce statistically accurate forecasts of the INR/USD rate benchmarking against several linear autoregressive models. Kiani and Kastens (2008) generated higher forecasting accuracy for GBP/USD and JPY/USD rates with feedforward and recurrent NNs comparing to several ARMA models. Although ANN achieved success in FX rates forecasting due to its nonlinearity, robustness and adaptivity, it has disadvantages and limitations such as overfitting, lack of interpretability, difficulty to handle qualitative factors, and local minimum problems often incurred when adopting the empirical risk minimization principle to solve the learning task.

To overcome the latter problem, support vector machine (SVM) was introduced and has been gaining popularity. SVM minimizes structural risks as opposed to empirical risks. Structural risk minimization is an inductive principle for model selection used for learning from finite training datasets. It describes a general model of capacity control and provides a trade-off between hypothesis space complexity and the quality of fitting the training data. Tay and Cao (2001) compared the feasibility of SVM and Back Propagation Neural Network (BPNN) in financial time series forecasting and concluded that SVM outperformed BPNN. Kamruzzaman *et al.* (2003) showed SVM to be a powerful tool for predicting six FX rates against Australian Dollar and achieved superior performance than ANN and ARIMA-based models. Ince and Trafalis (2006) combined ARIMA and SVM to predict the directional movement of the EUR/USD rate. The proposed model outperformed the logit and probit models. Ullrich *et al.* (2007) used SVM for algorithmic trading system with a variety of FX rates including EUR/USD. The results indicated that SVM outperformed ANN and other traditional techniques. Brandl *et al.* (2009) used genetic algorithms (GA) for variable selection and implemented SVR. The proposed model outperformed a NN, an OLS regression and an ARIMA model on monthly EUR/USD, USD/JPY, and USD/GBP rates.

In recent literature, there is a growing number of novel and hybrid approaches, combining the advantages of various methods including ANN and SVM. Gradojevic (2007) combined artificial neural networks and fuzzy logic controllers to obtain the optimal daily currency trading rules. Khashei *et al*. (2008) combined ANN and fuzzy regression to overcome the limitations in both ANN and fuzzy regression models and have shown improvement in prediction accuracy. ANN has also been integrated with ARIMA and fuzzy logic by Khashei et al. (2009) to overcome the linear and data limitations of ARIMA model. On a similar framework, Khashei & Bijari (2011) proposed a novel hybridization of ANN and ARIMA model such that the model is able to handle both linear and nonlinear components of time series data. A distance-based fuzzy time series (DBFTS) model was proposed by Leu *et al.* (2009) predict FX rates, which uses the distance between two fuzzy logic relationships (FLRs) in selecting prediction rules. In another hybrid model, Pai *et al*. (2010) combined the rough set theory (RST) based model and SVM to extract the rules of FX rate changes. An immune algorithm and Tabu search (IA/TS) method was used for variable selection. Kablan and Ng (2011) introduced an adaptive neuro-fuzzy inference system for financial trading, which learns to predict FX price movements of tick by tick data.

Deep learning has been used to achieve state-of-the-art results for solving difficult AI tasks. However, much focus in deep learning has been on developing models for static data, such as computer vision, and not so much on time series data. In recent time series analysis, deep learning was frequently used for video recognition (Chen, 2010; Taylor *et al*., 2010), speech recognition (Lee *et al*., 2009; Graves *et al*., 2013 May), and music recognition (Hamel & Eck, 2010; Dieleman *et al*., 2011). Only a limited number of papers focused on financial markets. Zhang (2014) utilized deep belief networks (DBN) to forecast FX rates and found that these networks performed better than other classical approaches. Deng *et al.* (2016) introduced the concept of fuzzy learning into deep learning and built fuzzy deep neural network (FDNN) model. The model was applied to the task of financial signal prediction using tick data of Shanghai Financial Index future (IF) and was concluded to improve the performances of shallow learning systems.

Methodology Overview

This project will modify and implement the model suggested by Plakandaras *et al.* (2015) as the benchmark model in order to study if the application of deep learning is able to improve the prediction accuracy. The benchmark model consists of time series decomposition method – EEMD, feature selection method – MARS, and forecasting model – SVR. An overview of the aforementioned methods will be presented in this section. The benchmark model, EEMD-MARS-SVR, firstly extracts of the long-run and short-run dynamics of time series by EEMD; then applies feature selection by MARS on both long-run and short-run data; next employs SVR to fit on both datasets to produce two forecasts; lastly sums two forecasts to generate final prediction. The model was reported to constantly produce superior results than random walk model in out-of-sample forecasting. It was also claimed to reach the highest directional accuracy at 74.6%. The model performance makes it a suitable benchmark case for future comparison with the proposed model applying deep learning.

The modification in this project consists of 2 extra stages after EEMD before MARS feature selection. Firstly, Granger Causality Test (GCT) was implemented on both long-run data and short-run data to select currencies or other investment instruments that significantly correlates with the target currency. Such method was carried out in order to reduce the number of independent variables, as each investment instrument consists of too many raw variables to include in one model. Afterwards, instead of choosing lag 1 data, Vector Autoregression (VAR) was used to select appropriate lag number. Hence the benchmark model in this project would be EEMD-GCT-VAR-MARS-SVR.

Deep learning model follows the classic deep feedforward networks with random grid search tuning method for parameters' values.

GCT: Granger Causality Test

Granger causality test is a statistical hypothesis test for determining if one time series is correlated with another. Suppose two time series are X and Y, then X is said to Granger-cause Y if it can be shown that, through a series t-test and F-test on lagged values of X, X is statistically significant in predicting Y.

Mathematically, a autoregression is fitted with previous Y values and X values.

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_m y_{t-m} + b_p x_{t-p} + \cdots + b_q x_{t-q} + \varepsilon_t$$

According to F test, one can determine if X can add explanatory power to predicting y_t.

VAR: Vector Autoregression

VAR generates the univariate autoregressive model by fitting its p lagged values, called VAR with p lags.

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_p y_{t-p} + \varepsilon_t$$

For each model with its p lagged values, AIC was used as a reference to determine the best number of p.

EEMD: Ensemble Empirical Mode Decomposition

EEMD, proposed by Wu and Huang (2009), is a modification of EMD (Huang *et al*., 1998). EMD decomposes an oscillating data series into a number of Intrinsic Mode Functions (IMFs) or modes.

To be considered as an IMF, a data series must satisfy two conditions: (i) the number of extrema and the number of zero-crossings is either equal or differs only by one; and (ii) the mean value of the upper and lower envelope is zero at any point. Cubic spline interpolation is applied on both local maximums and local minimums to form upper envelope and lower envelope respectively. The procedure of creating IMF is called sifting, which is the repetition of generating upper and lower envelope, taking their average as the envelope mean, and subtracting the envelope mean from the data series until properties of IMF are satisfied, as shown in *Figure 1*. Certain stopping rules will be applied to ensure sifting termination. The number of extrema will decrease as the procedure continues, so that the series is sequentially decomposed from the highest frequency component IMF_1 to the lowest frequency component IMF_n. Hence the advantage of EMD is to extract high frequency data and low frequency data such that researchers could analyse the series separately. It also does not require data linearity or stationarity, making it suitable for financial market data. *Figure 2* shows the procedure of producing IMF_1 and IMF_2; and *Figure 3* shows an example of the final decomposition result of a data series.

One of the major drawbacks of EMD is mode mixing (Huang & Wu, 2008), which implies either an IMF consisting of data series of disparate frequencies or a data series of the same frequency appearing in different IMFs, and usually causing intermittency of the analysis. Hence, EEMD is introduced to overcome such problem. The difference of EEMD and EMD is the addition of white noise to the original data series and averaging the results of EMD. Different white noise series will be added to the original series generating many new series, each of which will be then applied with EMD. The average of the ensemble of IMFs with same index from every series decomposition will be the final IMF for each corresponding index (i.e. the average of the first IMFs from every series decomposition is the final first IMF and so on).

After producing final IMFs, first few IMFs will be added to represent the short-run dynamics of FX while the rest IMFs added to represent the long-run dynamics. The tipping point – IMF index that separates the short-run and long-run dynamics – is the first IMF where the energy compared to its former IMF rises (Moghtaderi *et al.*, 2013). Energy is calculated as

$$E^i \triangleq \sum_{t=1}^{n} \left|IMF_t^i\right|^2, 1 \leq i \leq L$$

where L is the total number of IMFs. Two dynamics data are modeled and forecasted independently.

MARS: Multivariate Adaptive Regression Splines

MARS, proposed by Freidman (1991), is a non-parametric form of piecewise nonlinear regression. Unlike the linear regression which fits the whole dataset using one parametric linear function, MARS splits the datasets into subgroups and each subgroup is fitted by a model locally. Each of these local models are called basis function, which form splines that are interconnected by points called knots. Basis function is either a constant, a hinge function of the form $\max(0, x - knot)$ or $\max(0, knot - x)$, or the product of two or more hinge functions. The MARS model has the form

$$y = \sum_{i=1}^{m} \beta_i B_i(x) + e$$

where $B_i(x)$ is the ith basis function and m is the number of subgroups.

The formation process of MARS model is similar to stepwise regression with both forward phase and backward phase. The forward phase arbitrarily selects a knot that falls within the range of each independent variable to define a pair of basis functions. At each step, the model adapts the knot and its corresponding pair of basis functions that provides the maximum reduction in sum-of-squares error (SSE). This process of adding basis functions continues until the change in SSE is too small or the maximum number of basis functions is reached. Such resulting model usually overfits the dataset. The backward phase serves to prune the model by removing one of the paired basis function that contributes the most to generalized cross validation (GCV) at each step until stopping criteria is reached.

$$GCV = \frac{SSE}{N \times \left(1 - \frac{(\#BFs + Penalty \times (\#BFs - 1)/2)}{N}\right)^2}$$

where #BFs is the number of basis functions in the model, Penalty is a constant, N is the number of observations. GCV penalizes not only the number of basis functions but also the number of knots. Hence backward phase attenuates the overfitting problem by sacrificing a bit of model accuracy. An example illustration of MARS is shown in *Figure 4*.

After model completion, the variables in the model are considered as the selected variables. Thus feature selection is realized.

SVR: Support Vector Regression

SVR, proposed by Smola and Vapnik (1997), is an extension of support vector machine (SVM), which is a classification paradigm. Analogous to SVM, SVR is an optimization problem with constraint called the loss function. A number of loss functions can be adopted for the formulation of SVR, such as the Laplacian, Huber's Gaussian, and most commonly ε-insensitive. When ε-insensitive is the loss function, for example, the algorithm aims to find a function $f(x)$ such that it deviates at most ε units from the actual value for all data, and in the meanwhile, keeps the deviation as small as possible. That is, errors within the range of [0, ±ε] will be accepted and restrained as small as possible, while beyond the boundary will not be tolerated. This could be important if an investor aims not to lose more than ε money when dealing with FX, for instance. One way to ensure such formulation is to minimize the norm, as shown below.

$$\text{minimize } \frac{1}{2}\|w\|^2$$

$$\text{subject to } \begin{cases} y - f(x) \leq \varepsilon \\ f(x) - y \leq \varepsilon \end{cases}$$

However, such optimization problem might very likely not be feasible. Similar to the "soft margin" of SVM, slack variables, ξ_i and ξ_i^*, could be introduced to set a degree of deviation tolerance to tackle infeasibility problem. The optimization formulation is then transformed to

$$\text{minimize } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$

$$\text{subject to } \begin{cases} y - f(x) \leq \varepsilon + \xi_i \\ f(x) - y \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases}$$

where C is the tolerance level and n is the number of observations. An illustration is presented in *Figure 5*.

The general form of SVR can be written as

$$f(x) = b + \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x, x_i)$$

where α, α_i are Lagrange multipliers and $K(x,x_i)$ is the kernel function. Common kernel functions are linear, polynomial, and radial basis function.

Deep Learning

Deep learning is a broad stream of machine learning algorithms which includes many substreams such as deep neural networks, convolutional deep neural networks, deep belief networks, and recurrent neural networks. In this project, deep feedforward networks – the quintessential deep learning models – were used to perform prediction. The goal of a feedforward network is to approximate some function f^*, named activation function. For example, for a classifier, $y = f^*(x)$ maps an input x to a category y. A feedforward network defines a mapping $y = f(x;\theta)$ and learns the value of the parameter θ that result in the best function approximation. These models are called feedforward because information flows through the function being evaluated from x, through the intermediate computations used to define f, and finally to the output y. While the simplest feedforward network composes of only 1 layer and 1 neuron as shown in *Figure 12*, the name "networks" arises from the fact that the model is typically represented by composing together many layers of functions, with each layer having multiple neurons, as shown in *Figure 13*. The overall number of layers gives the depth of the model. Hence the name "deep". Each neuron represents an activation function that takes input x and outputs $y = f(W^T x) = f(\Sigma w_i x_i + b)$, where W represents the weights and b represents the bias. At each layer, there will be a bias unit that will be added to each activation function as the intercept term. W and b together forms the parameter θ as aforementioned. The output from each neuron in one layer forms the input of the next layer. At the output layer, which is the last layer, one value will be generated and this value will be the predicted value of the model.

To train the model, suitable cost function, or objective function, need to be set up. Usually, it could be the Euclidean distance or cross entropy of the network output and target value. For the case of Euclidean distance, the cost function will be the following form

$$C(\theta) = \sum_{i=1}^{m} \left(f\left(x^{(i)}; \theta\right) - y^{(i)} \right)^2$$

For the case of cross entropy between the training data and model distribution, equivalently known as maximum likelihood method, the cost function is simply the negative log-likelihood. Such cost function is given by

$$C(\theta) = -E_{x,y \sim \tilde{p}_{data}} \, log \, p_{model}(y|x)$$

Stochastic gradient descent is usually applied to minimize the cost function, which is to find the optimal weights and biases. However, due to the nature of non-convex cost function in neural networks, such method has no convergence guarantee, and is sensitive to the values of the initial parameters. There are also numerous parameters in deep learning that need to be properly set. Hence, hyperparameter tuning is needed for deep learning. Given a range of values, grid search has a higher chance to find the local or even global minimum. However, due to the large size of datasets and problem complexity, grid search will require much longer time to find the minimum. In this project, random grid search was implemented to shorten the computational time. Besides the given range, certain stopping rules were set to terminate the computation when it is considered sufficiently close to the best it can perform.

Data Collection and Preprocessing

The datasets for this project are composed of data from 8 major categories, namely FX spot rates, commodities, indices, bonds, FX futures, macroeconomics, as well as technical indicators. Due to the modern interconnectivity of financial markets across different asset classes, FX market are not only influenced by currencies, but also digests trading information from other markets. From market experience, it is justifiable to include commodities, indices, bonds, and FX futures in the model. Besides, FX rates are highly sensitive to macroeconomics data, especially important ones from major countries. Lastly, technical indicators are popular quantitative tools to extract insightful information from financial data. A summary of all items in each category is listed in Table 1. Details of each category and corresponding preprocessing methods are discussed below.

FX Spot Rates

Hourly FX rates are treated as the studying object of this project. Since the majority free historical rates are in daily format, it costed quite a while to find free intraday data on the internet. Bloomberg has been a major source of data used by other research papers. However, it provides only 140 days of intraday data for free, which is too few for the purpose of this project. Dukascopy is a useful website providing free intraday FX as well as other instruments data in hourly format. However, the prices are bid and ask prices but not current prices, which does not help for the purpose of predicting spot rates. Eventually, HistData.com is chosen as the data source. It provides free intraday current prices in minutes including all of the aforementioned asset classes. 6 major FX were downloaded from the website, each contains date, time, open price, high price, low price, close price, and volume. The date and time follows EST time zone without daylight savings adjustment.

However, missing values exist in the datasets. Specific methods were applied to convert these datasets with missing values to hourly data. For data instances within an hour, the highest price among the high prices is the high price of that hour, and the lowest price among the low prices is the low price of that hour. If the first instance starts at 00 minute, the open price of the hour is the open price of the first instance. Otherwise if the last instance is at 59 minutes, the open price of the hour is the close price of the last instance. If not, the open price of this hour is set to be the average of last instance's close price and next instance's open price. Similarly, for close price, if the last instance is at 59 minutes, the close price of the hour is the close price of the last instance. Otherwise if last instance is followed by 00 minute, the close price of this hour is the open price of next hour. When it is not followed by 00 minute, the close price is set to be the average of the last instance's close price and the next instance's open price. There are cases where the difference of the hour digits between two instances exceeds 2. For example, one instance is at 1:25 and the next one is at 3:40. For such case, the open price at 2:00 will be the average of close price at 1:25 and the open price at 3:40. The close price will be the same as the open price. The high and low price will be the high and low price for 1:25 and 3:40. When the difference is 3 or more, the open, close, low, and high prices in between will be the same as the first corresponding prices. As there is no perfect solution for missing values, such method is deemed suitable and reasonable in this context. Table 2 shows the time range and gap of every FX.

Commodities

Oil is considered correlated with FX rates, especially for currencies that depends on the import or export of oil. For example, Canadian dollar tends to appreciate against other currencies when oil price goes up, i.e. USD/CAD decreases, for Canada is a net oil exporter that will create more revenues as the price increases. Similarly, gold and silver also have high correlation with FX rates.

For example, Australian dollar will appreciate against other currencies when gold price goes up, i.e. AUD/USD increases, for Australia is one of the largest gold producer in the world.

Data was downloaded from the same source as FX rates. Hence the format and missing value problem persist. The same method applied to convert format and handle missing value. Details are presented in Table 3.

Indices

Equity market can provide valuable insight into FX market. The interaction need to be considered from a macroeconomic viewpoint. When the equity market is performing well or investors have a positive expectation of it, more capital will flow into the equity market and the first thing will be buying U.S. dollar which can then be used to purchase stocks. The demand for U.S. dollar increases caused the U.S. dollar to appreciate against other currencies.

Data collection and preprocessing follows the same procedure as the preceding two types. Details are shown in Table 4.

Technical Indicators

Technical indicators are calculated based on the datasets for the aforementioned 3 asset classes after handling missing values. Three types of technical indicators are calculated, namely trend, volatility, and momentum. Specific technical indicators in each category are selected based on their popularity in both researchers and practitioners. Components of each type are summarized below.

- Trend: Average Directional Index, Moving Average Convergence Divergence, Aroon.

- Volatility: Bollinger Bands, Average True Range, Chaikin Volatility

- Momentum: Relative Strength Index, Stochastic Momentum Index, William % R

The technical indicators are applied on original datasets instead of datasets after EEMD, since the processing time for EEMD is too long to finish the program within an acceptable time frame in order to provide timely prediction for the next hour. The computational power of the program limits the possibility of running EEMD each hour. Hence, when technical indicators are applied on original data, the program could directly calculate those technical indicators in a very short time, which enables timely prediction. R package TTR was used to calculate the technical indicators.

Macroeconomics

Macroeconomics is the primary factor that causes fluctuation in FX market. Health condition of one country's economy determines the strength of the corresponding currency. Healthy economy will boost the appreciation of that currency. Hence trading decisions are made by traders based on their views of the economy, given by numerous important economic indicators. A macro was written to download all the macroeconomic indicators from Bloomberg. Table 5 summarized all the macroeconomic indicators used for every country. Among them, the Citi Economic Surprise Indices (CESI) measure the surprises relative to market expectations. A positive reading means that data releases have been stronger than expected and vice versa.

For some downloaded files, missing values exist as Bloomberg does not have relevant data. Investing.com served as the second source of data to fill out those missing values, if available. Indicators that were not able to find supplementary values from second data source are then discarded.

Besides the actual values, corresponding forecasted values were downloaded as well. Forecasted indices are provided by economists and analysts in the financial markets who use Bloomberg on a voluntary basis. Bloomberg will then calculate the mean, median, minimum, and maximum based on those forecasts. The mean value was used as the final forecasted number. Since the unit of each economic index is different, standardization was carried out for each macroeconomic indicator by calculating the surprise index, like CESI, as the difference of actual value and forecasted value divided by its sample standard deviation

$$Surprise\ Index = \frac{A_{kt} - F_{kt}}{\hat{\sigma}_k}$$

where A_{kt} is the actual value for macroeconomic indicator k at time t, F_{kt} is the mean of forecasts, and $\hat{\sigma}_k$is the sample standard deviation of $A_k - F_k$. For a few indicators with no forecasts, the original values were used.

One of the major issues dealing with macroeconomics is about time zone. Since the FX data follows EST time zone and did not apply day light savings rule, macroeconomic data have to adjust accordingly in order to fit into the datasets. All macroeconomic data retrieved from Bloomberg follows EST time zone but also adjusted to the daylight savings. As daylight savings in different countries for each year are all different, the time conversion becomes much complicated. The process took about 2 weeks to finish. Besides, some economic variables are announced at 15 minutes or 30 minutes. Such timings are all changed to be the previous 00 minute.

Another issue is the frequency of macroeconomics announcement. For most of the indicators, announcements are made on monthly basis, with a minority on quarterly and weekly basis. However, FX rates are hourly data. Hence all the macroeconomics data need to be converted to hourly basis. Cubic spline interpolation is a common way used by economists to disaggregate low frequency data to high frequency data. However, it is not acceptable in this case. While it may achieve the goal to convert to hourly data, it is actually using the information in the future. For the values between two announcement dates, a cubic polynomial is plotted to connect the two points. Yet the spline is created using the value of both points. However, the second point is actually a future value that should not be used to calculate the values in between the two dates. Hence such method is breaching the rule with future information and should not be applied here. For now, no better method could provide acceptable results without using information in the future than simply repeating the value till the next announcement date.

Model Construction and Prediction Results

Pre-Training Setup

First of all, EEMD was applied on the FX closing prices. The number of IMFs was set to be 16, i.e. 15 IMFs and 1 residual, as it was the minimum number to produce a smooth curve for the residual. The EEMD graph of each FX is presented in *Figure 6 – 11*. The tipping point of short-run and long-run data is 4 based on the calculated energy. Hence the first 3 IMFs were summed to be the short-run data, and the rest IMFs plus residual were summed to be the long-run data.

After data preprocessing and merging all datasets, there are in total 517 variables. To reduce the number of variables and more importantly boosts the speed of future model fitting, Granger Causality Test was used to select the correlated investment instruments. F-test will show the significance of different instruments and significant instruments are kept onwards. Here, the test was applied on the instrument prices. If one instrument price is shown to be correlated with the target currency price, then the whole series of variables related to such instrument will be added to the model. The benchmark p-value was set to be 0.05. The variables related to the target currency will be included without Granger Causality Test by default. The results are summarized in *Table 6 – 11*.

Afterwards, VAR was applied to the dependent currency to select the number of lags. AIC was used to determine the best number of lags. The maximum number of lags to be considered was set to be 12. Results were shown in *Table 12*. Once the number of lags is determined, all of the previously selected variables will include lag 1 till that specific lag number, for both long-run data and short-run data.

MARS was then applied to further select variables. *Table 13* summarizes the number of input variables selected by MARS. It could be observed that the number of variables selected for the long-run component is always 1, which is the closing price. Besides, it is always less than the number of variables selected for short-run data as well. That is, in general, the long-run component can be modelled with fewer explanatory variables than the short-run component. Explicit variables for each currency could be found in *Table 14*.

Model Training Overview

At this stage, two different kinds of models would be trained – SVR and deep learning. For SVR models, the independent variables would be the ones that were selected after MARS. For deep learning models, the independent variables would be two sets: one is the same as for the SVR (EEMD-GCT-VAR-MARS-DL); another will be the variables after Granger Causality Test and VAR but without MARS so as to utilize the fact that deep learning model is better or more accurate with more independent variables (EEMD-GCT-VAR-DL). Therefore, two sets of deep learning models would be trained for each FX.

Training data includes prices since 2010 till 2015. Testing data will be the prices in 2016.

For both models, cross validation was not implemented due to the nature of time series. Cross validation will partition the original training data into several subsets and train the model using several subsets to predict the remaining subset. When it is using subsets in the future to predict the history, it violates the rule of not using future information. Besides, the model should perform the best on the history so as to predict the near future, while the model prediction result after cross validation composes of prediction results on the history and such model does not necessarily have a better performance to predict the future than the former. To further elaborate, given a set of parameters, one of the cross-validation models will use data from 2011 till 2015 as training data so as to predict the data in 2010. Such model uses future prices to predict historical prices and hence should not be considered to evaluate the given parameters. And the model robustness does not make sense in the context of time series as a time series model has to be updated after some time so as to capture the latest hidden information, which is different from a non-time-series prediction model that could be used back and forth for even years. Other than the aforementioned reasons, another practical reason is that cross validation takes too long to implement due to the size of the datasets.

The most important stage during model training is parameter tuning. For both models, mean absolute error (MAE) on testing data was used as a reference to tune the parameters.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|$$

It is the most direct and clear way to check the model accuracy for FX prediction, for the market reacts to the change of prices rather than its base value. Hence the goal is to find a set of parameters that minimize the models' MAE. There are numerous techniques for global optimization. In this project, different techniques were used for SVR and deep learning. For SVR, generalized simulated annealing was used to minimize MAE. It is tested by Mullen (2014) that the generalized simulated annealing is most capable of consistently returning a solution near the global minimum of each test function and one of the fastest algorithms to reach the minimum as well. Hence, the same function as used in Mullen's research paper – GenSA from the GenSA package – was used for SVR parameter tuning. For deep learning, it is briefly discussed in the Methodology part that random grid search would be used for parameter tuning. To add on, another practical reason is that random grid search would be faster than other traditional tuning methods. In this project, time is a main issue as training usually takes days to finish. Besides, it is also supported by Bergstra and Bengio (2012) that random grid search is quite efficient and stable to find a model with good results. For both models, the range of parameters will be predetermined based on experience and parameter tuning will only considered values within the range. Although the global minimum may not lay in the range, it is deemed unlikely and will not be discussed in this project.

SVR Model Training and Results

There are three parameters need to be determined for SVR, namely *cost*, *gamma*, and *epsilon*. The *cost* factor is a parameter that allows one to trade off training error versus model complexity. A small value for *cost* will increase the number of training errors, while a large *cost* will lead to a behaviour similar to that of a hard-margin SVR. The value of *epsilon* determines the level of accuracy of the approximated function. It relies entirely on the target values in the training set. If *epsilon* is larger than the range of the target values, there will be fewer support vectors and the result will not be good. If epsilon is zero, it may result in overfitting. The parameter *gamma* is from the radial kernel function. Technically speaking, large *gamma* leads to high bias and low variance models, and vice-versa. The range of each parameter is summarized in *Table 15*. Initial values were also set for each parameter: cost = 1, gamma = 0.1, and epsilon = 0.1. With generalised simulated annealing, the best parameters for each FX were found and summarized in *Table 16*. It should also be mentioned that the tuning stage took quite a long time. For each FX, the parameter tuning for long-run data would usually take 4 – 7 hours and 12 – 19 hours for short-run data. With the parameters determined, the best models were then built on training data and then several statistical metrics were calculated on testing data to further evaluate the model. Besides MAE, mean squared error (MSE), root mean squared error (RMSE), root mean squared logarithmic error

(RMSLE), mean absolute percentage error (MAPE), and directional symmetry (DS) were also computed. Thereinto, DS was only computed for the final prediction while not on separate long-run and short-run data.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$

$$RMSLE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(log(\hat{y}_i + 1) - log(y_i + 1))^2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\hat{y}_i - y_i}{y_i}\right)^2$$

$$DS = \frac{100}{n}\sum_{i=1}^{n} d_i\, , where\ d_i = \begin{cases} 1\ if\ (y_i - y_{i-1})(\hat{y}_i - \hat{y}_{i-1}) > 0 \\ 0\ \ otherwise \end{cases}$$

Thereinto, DS measures the percentage of the times that the model correctly forecasts the future direction of the exchange rate. Directional forecasting is of key interest to market participants, since trading decisions on whether to go long or short on a currency depend on whether an appreciation or depreciation is expected rather than the exact future value of the exchange rate. The model accuracy for long-run testing data, short-run testing data, and final prediction is reported in *Table 17*.

Deep Learning Model Training and Results

Compared to SVR, deep learning has much more parameters and parameter selection would be more difficult and slower. For this project, 7 representative parameters were selected for tuning, namely *activation function*, *layers*, *neurons*, *epochs*, *input dropout ratio*, *L1 regularization*, and *L2 regularization*. “Rectifier” and “RectifierWithDropout” were chosen as candidates for *activation function* due to their proven superior accuracy comparing to other functions. The rectifier function is mathematically given by

$$h^i = max\left(w^{(i)T}x, 0\right) = \begin{cases} w^{(i)T}x & w^{(i)T}x > 0 \\ 0 & else \end{cases}$$

where $w^{(i)}$ is the weight vector for the i^{th} hidden unit, and x is the input. “RectifierWithDropout” is to address the problem of overfitting by randomly dropping units (along with their connections) from the neural networks during training. Intuitively, this forces the network to be accurate even in the absence of certain information. It prevents the network from becoming too dependent on any one (or any small combination) of neurons. An example of dropout in neural networks is presented in *Figure 14*. For *layers*, it was set to be 1 for long-run data as there is only 1 independent variable for each FX. For short-run data, it will be from 2 to 10 as there are more independent variables. The number of layers is not set to be too large as it will extensively increase the computation time. For long-run and short-run data using independent variables without MARS feature selection, the number of layers were both set to be from 2 to 10. For *neurons*, each layer will have 10 to 100 neurons. The number of neurons is not too many due to the same reason. *Epochs* stand for the number of times the dataset should be iterated. To find weights and biases, stochastic gradient descent works by picking out a randomly chosen mini-batch of training inputs, and training with those. Afterwards another randomly chosen mini-batch will be chosen and trained upon. The process continues until the training data are exhausted, which is said to complete an epoch of training. Then the process will start over with another new epoch. It will usually take thousands of epochs for the stochastic gradient descent to converge on a combination of weights and biases with an acceptable level of accuracy. Hence, *epochs* were set to be between 0.1 and 10000. *Input dropout ratio* is the percentage of inputs that will be dropped out from the training process, which is also beneficial to avoid overfitting. In this project, it is chosen from 0 to 0.3. Apart from input dropout and units dropout, *L1 regularization* and *L2 regularization* are also methods to improve generalization. Similar to lasso regression, *L1 regularization* is implemented by augmenting the cost function with the absolute magnitude of all weights in the neural network. In other words, for every weight w in the neural network, $\lambda|w|$ is added to the cost function, where λ is the shrinkage parameter and is need to be set. The *L1 regularization* has the intriguing property that it leads the weight vectors to become sparse during optimization. It will cause many weights to become 0. As for *L2 regularization*, similar to ridge regression, squared magnitude of all weights in the neural network – $\frac{1}{2}*\lambda w^2$ – is added to the cost function. Hence *L2 regularization* penalizes "peaky" weight vectors and smooths the weight vectors to be diffused. It will cause many weights to be small. The shrinkage parameter in *L1* and *L2 regularization* were set to be between 0 and 0.001. *Table 18* summarized the aforementioned parameter ranges. It is also worth mentioning that the tuning process would usually take 3 days to finish for 1 FX.

After random grid search, the optimal parameters for each model of each FX are summarized in *Table 19*. The model accuracies for long-run testing data, short-run testing data, and final prediction for both datasets, with or without MARS, are reported in *Table 20* and *Table 21*.

Base Model Training and Results

To better compare the model accuracies, 3 base models were trained as well, namely random walk (RW), ARIMA, and GARCH. The orders of the autoregression, differences, and the moving average in ARIMA were iteratively determined according to the minimized AIC. The same method was applied to GARCH as well to determine its parameters. The model accuracy results on testing data were summarized in *Table 22*.

Results Comparison

Comparing *Table 17*, *Table 20*, and *Table 21* across the evaluation metrics except DS, it is clear to see that EEMD-GCT-VAR-DL performed worse than EEMD-GCT-VAR-MARS-DL and EEMD-GCT-VAR-MARS-SVR for all 6 currencies. For DS, the direct prediction from all 3 models performed poorly, with lower than 50% correctness. Although a reverse direction from the prediction could reach more than 50% correctness, the results were still not satisfying. Comparing with EEMD-GCT-VAR-DL, EEMD-GCT-VAR-MARS-DL has an average 5 ticks smaller error for EURUSD, 8 ticks for GBPUSD, 17 ticks for USDJPY, 37 ticks for AUDUSD, 5 ticks for USDCHF, and 7 ticks for USDCAD. The corresponding percentage improvements are 39.6% for EURUSD, 34.4% for GBPUSD, 59.2% for USDJPY, 80.5% for AUDUSD, 38.5% for USDCHF, and 38.8% for USDCAD. Hence it is safe to conclude that deep learning with MARS has a better prediction accuracy than deep learning without MARS. The extra independent variables did not boost the accuracy but hampered. The reason is hard to confirm but too many irrelevant variables will add noise to the model and cause more biases in the neural networks. Comparing EEMD-GCT-VAR-MARS-SVR, the proposed EEMD-GCT-VAR-MARS-DL model performed slightly better for 5 currencies except a big jump for GBPUSD, with an average 0.8 tick smaller error for

EURUSD, 282 ticks for GBPUSD, 0.08 tick for AUDUSD, 0.1 tick for USDCHF, and 0.7 tick for USDCAD. The corresponding percentage improvements are 8.8% for EURUSD, 95% for GBPUSD, 0.85% for AUDUSD, 1.3% for USDCHF, and 5.3% for USDCAD. A possible reason for a big jump seen in GBPUSD could be its high volatility during 2016. As the EU referendum was held in June 2016, the market reacts to the news related to the referendum quite rapidly since the beginning of 2016. Such idea leads to the conjecture that SVR is not able to predict rapid ups and downs closely like deep learning. As for JPYUSD, the EEMD-GCT-VAR-MARS-DL model did not outperform GCT-VAR-MARS-SVR with an average 0.4 ticks bigger error, which is 3.6% worse. However, overall, the proposed EEMD-GCT-VAR-MARS-DL model has a better prediction accuracy than the benchmark model GCT-VAR-MARS-SVR.

Next the proposed EEMD-GCT-VAR-MARS-DL model is compared with the base models in *Table 22*. It is surprising to see that EEMD-GCT-VAR-MARS-DL model did not have much better results than that of the base models. The improvement is tiny. Compared to the best base model for each currency, the EEMD-GCT-VAR-MARS-DL model has an average 0.04 tick smaller error for EURUSD, 0.05 tick for GBPUSD, 0.06 tick for JPYUSD, 0.2 tick for AUDUSD, 0.4 tick for USDCHF, and 0.04 tick for USDCAD. The corresponding percentage improvements are 0.5% for EURUSD, 0.4% for GBPUSD, 0.5% for USDJPY, 2.6% for AUDUSD, 4.8% for USDCHF, and 0.3% for USDCAD. This result may well reflect the noise in the short-term data. As this project studies the hourly prediction, it is a much shorter period compared with other projects which mostly focused on daily or monthly prediction. It is expected that the hourly data will contain low-value information that may hamper the model’s accuracy. Yet it is not expected to have such huge influence on the accuracy as the proposed model only has a tiny improvement over the random walk model. Hence using the proposed model to predict the hourly data does not provide significant values. This leads to the next stage of this project. Considering the usual noises spreading across the FX market, it is worth trying to see if the EEMD-GCT-VAR-MARS-DL model could perform better in certain conditional subsets of the hourly prices.

Further Model Training on Data Subsets

At this stage, several subsets were created from the whole dataset based on hourly return, volatility, and RSI. The idea was to see if the proposed model could perform better than base models on large price changes, eliminating the possible influences from the noise or untradeable hours. For hourly return, ±0.2% was chosen as the benchmark as those data represent around 10% of the whole dataset. For volatility, 24-hour volatility was computed and 0.2% (volatility higher than 0.2%) was set for EURUSD, USDJPY, AUDUSD, and USDCHF, while 0.15% (volatility higher than 0.15%) for GBPUSD and USDCAD. Again, they all represent around 10% of the original data. For RSI, any price whose corresponding RSI is above 80 or below 20 was extracted. With subsets ready, MARS was again implemented to select variables for each subset. The selected variables for each subset are summarized in *Table 23, Table 24,* and *Table 25*. Afterwards, deep learning and base models were trained on the new training data. Due to the experience from last stage, only variables selected after MARS would be included in the deep learning model. SVR is abandoned at this stage because of its low accuracy compared to the base models. The deep learning models' parameters for each FX are summarized in *Table 26*, *Table 27*, and *Table 28*, and accuracy results on testing data are summarized in *Table 29*, *Table 31*, and *Table 33*. The base models' accuracy is summarized in *Table 30, Table 32*, and *Table 34*.

This time, the testing results have shown promising superiority in the proposed EEMD-GCT-VAR-MARS-DL model. For the high/low-return subset, the proposed model has consistently performed better than the base models, and the improvement is relatively significant considering the nature of the FX market. Compared to the best base model for each currency, the EEMD-GCT-VAR-MARS-DL model has an average 6 ticks smaller error for EURUSD, 6 ticks for GBPUSD, 7 ticks for JPYUSD, 4 ticks for AUDUSD, 10 tick for USDCHF, and 7 ticks for USDCAD. The corresponding percentage improvements are 14.2% for EURUSD, 11.8% for GBPUSD, 17.1% for USDJPY, 13.0% for AUDUSD, 23.3% for USDCHF, and 14.9% for USDCAD. Hence it is safe to conclude that the proposed deep learning model could significantly improve prediction accuracy when the hourly price change is large. It could better grasp the changing information and react rapidly in its prediction.

For the high-volatility subset, the proposed deep learning model has shown promising result as well, except USDCAD. For the other 5 currencies, the deep learning model has also achieved better accuracy than the base model did. Compared to the best base model for each currency, the EEMD-GCT-VAR-MARS-DL model has an average 4 ticks smaller error for EURUSD, 6 ticks for GBPUSD, 5 ticks for JPYUSD, 5 ticks for AUDUSD, and 5 ticks for USDCHF. The corresponding percentage improvements are 12.0% for EURUSD, 16.4% for GBPUSD, 17.1% for USDJPY, 17.7% for AUDUSD, and 16.1% for USDCHF. Although the absolute change is smaller, the percentage improvement is still promising. As for USDCAD, the proposed model has an average 10 ticks higher error than the best performing base model – ARIMA(0,1,1).

For the high/low-RSI subset, the proposed model has the best performance improvement compared to the previous two subsets. Compared to the best base model for each currency, the EEMD-GCT-VAR-MARS-DL model has an average 15 ticks smaller error for EURUSD, 26 ticks for GBPUSD, 17 ticks for JPYUSD, 15 ticks for AUDUSD, 16 ticks for USDCHF, and 23 ticks for USDCAD. The corresponding percentage improvements are 43.2% for EURUSD, 48.0% for GBPUSD, 42.4%

for USDJPY, 44.2% for AUDUSD, 42.1% for USDCHF, and 49.2% for USDCAD. The directional accuracy is also constantly over 60%, with the highest reaching 71.1%. This has further manifested that the EEMD-GCT-VAR-MARS-DL model is consistent in outperforming base models during volatile periods, as three of the subsets all represent periods when volatility is high.

In conclusion, despite the small improvement, the proposed EEMD-GCT-VAR-MARS-DL model achieved better accuracy result than the EEMD-GCT-VAR-MARS-SVR model as well as the base models. The benchmark model EEMD-GCT-VAR-MARS-SVR failed to excel the prediction at hourly prices and produced worse accuracies than that of base models. Deep learning is believed to predict more accurately during short periods when prices change frequently. Besides, deep learning could further enhance its prediction accuracy for periods with high volatility. The EEMD-GCT-VAR-MARS-DL model has shown much superior performance than the base models. Hence deep learning could also handle rapid or big changes other than frequent changes. It was also shown that MARS feature selection could improve deep learning's prediction accuracy.

Conclusion

In this project, a hybrid combination of the EEMD time series decomposition into short- and long-run trend components that are then used to train a deep learning model to produce testing forecasts of exchange rates was studied. By decomposing the exchange rate time series and forecasting each component independently, the models were able to accommodate and focus on the different short- and long-run data separately and maximize prediction accuracy. The idea is from Plakandaras, Papadimitriou, and Gogas (2015), who proposed the EEMD-MARS-SVR model, which has been the benchmark model in this project with some modifications. Before MARS, GCT and VAR were applied to pre-select relevant currencies and suitable lags of the time series. Deep learning has been the focus of this project so as to test if deep learning could further improve the SVR's superior accuracy stated by the authors. The proposed deep learning model outperformed the benchmark model as well as base models in out-of-sample forecasting for all six currencies, namely EURUSD, GBPUSD, USDJPY, AUDUSD, USDCHF, USDCAD. However, the benchmark model did not show superiority over base models in the hourly data, yet deep learning performed better than base models, though the improvement is quite insignificant. Such result requires further examination of the model as well as the dataset. After subletting the original dataset, the data now focuses on only highly volatile periods, provided by high/low return, high 24-hour volatility, and high/low RSI. This time the proposed deep learning model outperformed the base model by a significant level, especially for RSI subset, which has decreased the error by nearly half. The result has again corroborated deep learning's dominance in the machine learning techniques. It also proved its prediction reliability in the FX market, which is an imminent area of application for deep learning.

Limitations and Recommendations for Future Work

Several limitations exist in this project. First of all, the data gathered from the online platform are not guaranteed to be accurate, for the website is not an official financial website like Bloomberg or Yahoo Finance. The source is one of few websites that provide free intraday data. Secondly, the data were provided in minutes, but not hours. Besides, there were quite a number of missing data within one hour, some even has gaps over 1 hour. Hence some missing value techniques were applied to solve this problem. However, such methods are not influence-free hence will more or less affect the model training and subsequent testing results. Another limitation is the data processing power of the laptop used for this project. As the deep learning model training is significantly slow, to complete the project in time, the independent data need to be reduced before model training. Hence GCT was applied. A higher-performance computer could achieve model training in a shorter time thus more independent variables could be feed into deep learning models. Furthermore, more combinations of models could be completed as well, such as models without EEMD. Due to the time limitation, only potentially accurate models were examined in this project.

For future work, researchers could try more complex deep learning models, such as recurrent neural networks, or use autoencoder for model training. It is also encouraged to apply other machine learning models other than SVR as comparison, such as fuzzy time series, string prediction model, etc. Besides, researchers could build models in a shorter time frame and use sliding window technique to build several models across the longer period to test the model more accurately. Furthermore, as FX correlates closely with countries' economy, which is reported by news frequently, researchers could also include news data into the model and convert textual information to numerical information. There has been relevant research on the influence of news on FX prices but not a holistic model that include news as part of its independent variables. Lastly, it is also encouraged to try deep learning on other market data, such as stocks prices, commodities prices, etc, which remains as an under-discovered area for the application of deep learning.

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Tables

Table 1

Summary of all independent variables

FX	Commodities	Indices	Technical Indicators	Macroeconomics
EUR/USD	WTI	S&P 500	ADX	See Table 5
USD/JPY	Brent Crude Oil	NASDAQ 100	MACD	
GBP/USD	Gold	EUROSTOXX 50	Aroon	
AUD/USD	Silver	NIKKEI 225	Bollinger Bands	
USD/CAD		FTSE 100	ATR	
USD/CHF		ASX 200	Chaikin Volatility	
			RSI	
			SMI	
			William %R	

Table 2

Summary of FX data

FX	Start Date	End Date	Mean Time Gap (minutes)	Maximum Time Gap (minutes)
EUR/USD	2010-01-03	2016-09-23	1.018596	178
USD/JPY	2010-01-03	2016-09-23	1.056343	162
GBP/USD	2010-01-03	2016-09-23	1.022938	207
AUD/USD	2010-01-03	2016-09-23	1.022337	166
USD/CAD	2010-01-03	2016-09-23	1.055968	242
USD/CHF	2010-01-03	2016-09-23	1.032539	164

Note: This is the summary of raw data before handling missing values.

Table 3

Summary of commodities data

Commodities	Start Date	End Date	Mean Time Gap (minutes)	Maximum Time Gap (minutes)
WTI	2010-11-14	2016-09-30	1.139343	408
Brent Crude Oil	2010-11-14	2016-09-30	1.237166	407
Gold	2010-01-03	2016-09-30	1.046087	395
Silver	2010-01-03	2016-09-30	1.107882	302

Note: This is the summary of raw data before handling missing values.

Table 4

Summary of indices data

Indices	Start Date	End Date	Mean Time Gap (minutes)	Maximum Time Gap (minutes)
S&P 500	2010-11-15	2016-09-30	1.411463	363
NASDAQ 100	2010-11-15	2016-09-30	1.115827	303
EUROSTOXX 50	2010-11-15	2016-09-30	1.30363	334
NIKKEI 225	2010-11-15	2016-09-30	1.569724	342
FTSE 100	2010-11-15	2016-09-30	1.012421	128
ASX 200	2010-11-15	2016-09-30	1.459719	300

Note: This is the summary of raw data before handling missing values.

Table 5

Summary of macroeconomic indicators for every country

Name of announcement	Start Date	End Date	Time (EST)	Frequency	Number of observations
U.S.					
CESI	2010-01-04	2016-11-01	00:00	D	1758
Consumer Confidence	2010-01-26	2016-09-27	08:00	M	81
CPI MoM	2010-01-15	2016-09-16	08:00	M	81
CPI YoY	2010-01-15	2016-09-16	08:00	M	81
Current Account	2010-03-18	2016-09-15	08:00	Q	27
Durable Goods Orders	2010-01-28	2016-10-05	10:00	M	81
GDP QoQ	2010-03-26	2016-09-29	08:00	Q	27
Industrial Production MoM	2010-01-15	2016-09-15	09:00	M	81
Initial Jobless Claims	2010-01-07	2016-09-29	08:00	W	352
Interest Rate	2010-01-27	2016-09-21	14:00	M	54
ISM Manufacturing	2010-01-04	2016-10-03	10:00	M	82
New Home Sales	2010-01-27	2016-09-26	10:00	M	81
Nonfarm Payroll	2010-01-08	2016-09-02	08:00	M	81
PMI	2010-01-04	2016-10-03	10:00	M	82
PPI MoM	2010-01-20	2016-09-15	08:00	M	81
PPI YoY	2010-01-20	2016-09-15	08:00	M	81
Retail Sales MoM	2010-01-04	2016-09-15	08:00	M	81
Treasury Bill 10 Years	2010-01-04	2016-09-30	00:00	D	1698
Trade Balance	2010-01-12	2016-10-05	08:00	M	82
Unemployment Rate	2010-01-08	2016-09-02	08:00	M	81
Eurozone					
CESI	2010-01-04	2016-11-01	18:00	D	1758
Consumer Confidence	2010-01-07	2016-09-29	10:00	M	81
CPI MoM	2010-01-15	2016-09-15	05:00	M	81
CPI YoY	2010-01-15	2016-09-15	05:00	M	81
Current Account	2010-01-26	2016-09-19	09:00	M	81
EONIA	2010-01-04	2016-10-04	13:00	D	1729
EURIBOR 3 Months	2010-01-04	2016-10-04	05:00	D	1732
GDP QoQ	2010-01-08	2016-09-06	05:00	Q	28
Industrial Production MoM	2010-01-14	2016-09-14	04:00	M	81
Interest Rate	2010-01-14	2016-09-08	06:00	M	81
PMI	2010-01-04	2016-10-03	03:00	M	82
PPI MoM	2010-01-06	2016-10-04	05:00	M	82
PPI YoY	2010-01-06	2016-10-04	05:00	M	82
Retail Sales MoM	2010-01-07	2016-10-05	04:00	M	82
Trade Balance	2010-01-15	2016-09-15	04:00	M	81
Unemployment Rate	2010-01-08	2016-09-30	05:00	M	81
ZEW Survey	2010-01-19	2016-09-13	04:00	M	81

Japan					
CESI	2010-01-04	2016-11-01	10:00	D	1758
Consumer Confidence	2010-01-19	2016-09-20	00:00	M	81
CPI MoM	2010-01-28	2016-09-29	18:00	M	81
CPI YoY	2010-01-28	2016-09-29	18:00	M	81
Current Account	2010-01-11	2016-09-07	18:00	M	81
GDP QoQ	2010-03-10	2016-09-07	17:00	Q	27
Industrial Production MoM	2010-01-28	2016-09-29	18:00	M	81
Interest Rate	2010-01-25	2016-09-20	22:00	D	1658
PMI	2010-01-28	2016-10-02	20:00	M	82
PPI MoM	2010-01-25	2016-09-26	18:00	M	81
PPI YoY	2010-01-25	2016-09-26	18:00	M	81
Retail Sales MoM	2010-01-27	2016-09-28	18:00	M	81
Trade Balance	2010-01-26	2016-09-20	18:00	M	81
Unemployment Rate	2010-01-28	2016-09-29	18:00	M	81
UK					
CESI	2010-01-04	2016-11-01	19:00	D	1758
Consumer Confidence	2010-01-28	2016-09-29	19:00	M	81
CPI MoM	2010-01-19	2016-09-13	03:00	M	81
CPI YoY	2010-01-19	2016-09-13	03:00	M	81
Current Account	2010-03-30	2016-09-30	03:00	Q	27
GDP QoQ	2010-03-30	2016-09-30	03:00	Q	27
Industrial Production MoM	2010-01-13	2016-09-07	03:00	M	81
Interest Rate	2010-01-07	2016-09-15	06:00	Q	81
PMI	2010-01-04	2016-10-03	03:00	M	82
PPI MoM	2010-01-08	2016-09-13	03:00	M	81
PPI YoY	2010-01-08	2016-09-13	03:00	M	81
Retail Sales MoM	2010-01-22	2016-09-15	03:00	M	81
Trade Balance	2010-01-12	2016-09-09	03:00	M	81
Unemployment Rate	2010-01-20	2016-09-14	03:00	M	81
Australia					
CESI	2010-01-04	2016-11-01	08:00	D	1758
Consumer Confidence	2010-02-01	2016-09-12	18:00	M	81
CPI QoQ	2010-01-26	2016-07-26	18:00	Q	27
Current Account	2010-02-28	2016-09-05	17:00	Q	27
GDP QoQ	2010-03-02	2016-09-06	17:00	Q	27
Interest Rate	2010-02-01	2016-10-03	22:00	M	82
PMI	2010-01-03	2016-10-02	16:00	M	82
PPI QoQ	2010-01-24	2016-07-28	18:00	Q	26
Retail Sales MoM	2010-01-06	2016-10-04	19:00	M	82
Trade Balance	2010-01-06	2016-10-05	19:00	M	82
Unemployment Rate	2010-01-13	2016-09-14	20:00	M	81
Canada					
CESI	2010-01-04	2016-11-01	00:00	D	1758
Consumer Confidence	2010-01-26	2016-09-20	09:00	M	81

CPI MoM	2010-01-20	2016-09-23	07:00	M	81
CPI YoY	2010-01-20	2016-09-23	07:00	M	81
Current Account	2010-02-26	2016-08-30	07:00	Q	27
GDP QoQ	2010-03-01	2016-08-31	07:00	Q	27
Industrial Production MoM	2010-01-05	2016-09-30	07:00	M	81
Interest Rate	2010-01-19	2016-09-07	10:00	M	81
PMI	2010-01-07	2016-10-07	10:00	M	82
PPI MoM	2010-01-05	2016-09-30	07:00	M	81
Retail Sales MoM	2010-01-22	2016-09-23	07:00	M	81
Trade Balance	2010-01-12	2016-10-05	07:00	M	82
Unemployment Rate	2010-01-08	2016-09-09	07:00	M	81
Switzerland					
CESI	2010-01-04	2016-11-01	18:00	D	1758
Consumer Confidence	2010-02-02	2016-08-04	02:00	Q	27
CPI MoM	2010-01-07	2016-09-06	03:00	M	81
CPI YoY	2010-01-07	2016-09-06	03:00	M	81
GDP QoQ	2010-03-02	2016-09-06	01:00	Q	27
Interest Rate	2010-03-11	2016-09-15	02:00	Q	27
PMI	2010-01-04	2016-10-03	02:00	M	82
PPI MoM	2010-01-15	2016-09-13	03:00	M	81
PPI YoY	2010-01-15	2016-09-13	03:00	M	81
Retail Sales YoY	2010-01-11	2016-09-01	03:00	M	81
Trade Balance	2010-02-04	2016-09-20	02:00	M	81
Unemployment Rate	2010-01-08	2016-09-09	00:00	M	81

Note: Time corresponds to EST time zone without daylight savings adjusted. For actual data, the time will have ± 1-hour difference as the announcement usually follows home country's time zone which will adjust to daylight savings. Time is changed to the previous 00 minute in order to fit hourly data. Frequency: Q – quarterly, M – monthly, W – weekly, D – daily. Germany economic variables are to be added in the next semester. Other macroeconomic indicators might be added as well in the future.

Table 6

Granger Causality Test Results – AUD (Significant Instruments Highlighted)

AUD_Long	F Value	P Value
CAD_Long	23.193	1.47E-06
CHF_Long	1.5106	0.2191
EUR_Long	22.684	1.91E-06
GBP_Long	7.9772	0.004738
JPY_Long	27.045	1.99E-07
BCO	1.5576	0.212
WTI	0.5325	0.4656
AUX	5.807	0.01597
ETX	2.8983	0.08868
JPX	2.0881	0.1485
NSX	3.0454	0.08097
SPX	4.4664	0.03458
UKX	6.6427	0.00996
XAG	3.1602	0.07546
XAU	1.4312	0.2316

AUD_Short	F Value	P Value
CAD_Short	1.9998	0.1573
CHF_Short	3.6997	0.05443
EUR_Short	6.00E-04	0.9801
GBP_Short	3.3263	0.06818
JPY_Short	8.9498	0.002776
BCO	3.1708	0.07497
WTI	8.4228	0.003708
AUX	0.6688	0.4135
ETX	0.2611	0.6094
JPX	0.1998	0.6549
NSX	0.2625	0.6084
SPX	0.0033	0.9539
UKX	0.4838	0.4867
XAG	0.4032	0.5255
XAU	1.184	0.2765

Table 7

Granger Causality Test Results – CAD (Significant Instruments Highlighted)

CAD_Long	F Value	P Value
AUD_Long	29.693	5.08E-08
CHF_Long	0.0953	0.7575
EUR_Long	16.287	5.45E-05
GBP_Long	7.2732	0.007
JPY_Long	7.6796	0.005586
BCO	4.101	0.04286
WTI	2.3539	0.125
AUX	6.9889	0.008205
ETX	4.9666	0.02585
JPX	3.6326	0.05666
NSX	8.9567	0.002766
SPX	8.0495	0.004554
UKX	6.8202	0.009017
XAG	4.2972	0.03818
XAU	2.1823	0.1396

CAD_Short	F Value	P Value
AUD_Short	1.8395	0.175
CHF_Short	5.4472	0.0196
EUR_Short	0.0461	0.8299
GBP_Short	2.7229	0.09892
JPY_Short	2000.8	2.20E-16
BCO	1.561	0.2115
WTI	0.0648	0.7991
AUX	0.5075	0.4762
ETX	1.83	0.1761
JPX	3.6513	0.05603
NSX	0.2008	0.6541
SPX	0.5719	0.4495
UKX	0.0081	0.9281
XAG	0.57	0.4503
XAU	0.6228	0.43

Table 8

Granger Causality Test Results – CHF (Significant Instruments Highlighted)

CHF_Long	F Value	P Value
AUD_Long	0.062	0.8034
CAD_Long	9.7712	0.001773
EUR_Long	1.7093	0.1911
GBP_Long	2.6517	0.1034
JPY_Long	3.3634	0.04666
BCO	2.2768	0.1313
WTI	0.4755	0.4905
AUX	3.6323	0.05668
ETX	1.7778	0.1824
JPX	2.2033	0.1377
NSX	1.203	0.2727
SPX	1.4142	0.2344
UKX	3.9456	0.047
XAG	1.1273	0.2884
XAU	0.6657	0.4146

CHF_Short	F Value	P Value
AUD_Short	1.1306	0.2877
CAD_Short	4.6111	0.03177
EUR_Short	8.4961	0.00356
GBP_Short	0.9684	0.3251
JPY_Short	4.2721	0.03875
BCO	5.3609	0.0206
WTI	9.4876	0.00207
AUX	4.1206	0.04237
ETX	3.2867	0.06985
JPX	8.00E-04	0.9781
NSX	1.4781	0.2241
SPX	1.2102	0.2713
UKX	2.5513	0.1102
XAG	1.00E-04	0.9903
XAU	0.0194	0.8892

Table 9

Granger Causality Test Results – EUR (Significant Instruments Highlighted)

EUR_Long	F Value	P Value
AUD_Long	23.961	9.85E-07
CAD_Long	29.782	4.85E-08
CHF_Long	11.091	0.0008676
GBP_Long	0.836	0.3605
JPY_Long	0.0416	0.8384
BCO	1.4068	0.2356
WTI	0.32	0.5716
AUX	3.9452	0.04701
ETX	1.67	0.1963
JPX	2.2608	0.1327
NSX	2.4461	0.1178
SPX	3.0905	0.07876
UKX	4.8607	0.02748
XAG	1.8768	0.1707
XAU	0.8337	0.3612

EUR_Short	F Value	P Value
AUD_Short	2.3174	0.1279
CAD_Short	1.5673	0.2106
CHF_Short	9.8606	0.001689
GBP_Short	14.834	0.0001175
JPY_Short	3.3013	0.06923
BCO	1.6097	0.2045
WTI	0.0255	0.8731
AUX	0.3151	0.5746
ETX	1.2623	0.2612
JPX	0.0301	0.8623
NSX	7.2432	0.00712
SPX	8.1602	0.004284
UKX	0.5362	0.464
XAG	0.6315	0.4268
XAU	2.2852	0.1306

Table 10

Granger Causality Test Results – GBP (Significant Instruments Highlighted)

GBP_Long	F Value	P Value
AUD_Long	3.0439	0.08104
CAD_Long	6.7778	0.009232
CHF_Long	18.169	2.02E-05
EUR_Long	0.3942	0.5301
JPY_Long	1.5618	0.2114
BCO	1.8877	0.1695
WTI	0.3884	0.5331
AUX	3.3864	0.06574
ETX	1.265	0.2607
JPX	2.3807	0.1228
NSX	2.0995	0.1474
SPX	3.072	0.07966
UKX	4.301	0.0381
XAG	4.2122	0.04014
XAU	2.8952	0.08885

GBP_Short	F Value	P Value
AUD_Short	0.0038	0.9506
CAD_Short	1.0879	0.2969
CHF_Short	2.7908	0.09481
EUR_Short	14.69	0.0001268
JPY_Short	0	0.9954
BCO	4.1142	0.04253
WTI	0.7016	0.4023
AUX	0.3176	0.573
ETX	0.6573	0.4175
JPX	0.912	0.3396
NSX	0.0546	0.8152
SPX	0.1715	0.6787
UKX	0.285	0.5934
XAG	0.3312	0.5649
XAU	3.5708	0.05881

Table 11

Granger Causality Test Results – JPY (Significant Instruments Highlighted)

JPY_Long	F Value	P Value
AUD_Long	21.811	3.01E-06
CAD_Long	1.152	0.2831
CHF_Long	0.2278	0.6331
EUR_Long	2.8013	0.09419
GBP_Long	2.6657	0.1025
BCO	0.0964	0.7562
WTI	0.0588	0.8085
AUX	1.7197	0.1897
ETX	1.5105	0.2191
JPX	1.7917	0.1807
NSX	0.3746	0.5405
SPX	0.6721	0.4123
UKX	2.9809	0.08426
XAG	1.3128	0.2519
XAU	0.2211	0.6382

JPY_Short	F Value	P Value
AUD_Short	0.0699	0.7914
CAD_Short	1602.9	2.20E-16
CHF_Short	4.1119	0.04258
EUR_Short	4.3584	0.03683
GBP_Short	7.6654	0.00463
BCO	3.6505	0.05606
WTI	0.0664	0.7966
AUX	0.0112	0.9157
ETX	1.7303	0.1884
JPX	2.7	0.1004
NSX	0.3226	0.5701
SPX	0.5407	0.4621
UKX	0.0455	0.831
XAG	2.2541	0.1333
XAU	1.5937	0.2068

Table 12

Number of lags selected by VAR for every FX

EURUSD	GBPUSD	USDJPY	AUDUSD	USDCHF	USDCAD
1	8	5	11	12	11

Table 13

Number of input variables selected by MARS for every FX

EUR/USD		GBP/USD		USD/JPY		AUD/USD		USD/CHF		USD/CAD	
Short -run data	Long -run data	Short -run data	Long -run data	Short -run data	Long -run data	Short -run data	Long -run data	Short -run data	Long -run data	Short -run data	Long -run data
8	1	7	1	5	1	4	1	9	1	5	1

Table 14

Independent variables selected from MARS for EURUSD

FX	Long-run	Short-run
EUR	EUR.Close	EUR.RSI EUR.SMI EUR.SMI.Signal EUR.pctB CHF.pctB GBP.tr EUR.macd EUR.DIn
GBP	GBP.Close	GBP.RSI GBP.RSI.2 GBP.tr GBP.tr.5 GBP.RSI.4 GBP.tr.2 GBP.pctB
JPY	JPY.Close	JPY.RSI JPY.RSI.2 JPY.RSI.4 GBP.tr JPY.DIn
AUD	AUD.Close	AUD.RSI AUD.RSI.2 AUD.RSI.4 AUD.RSI.10
CHF	CHF.Close	CHF.DIn CHF.DIn.3 CHF.RSI CHF.RSI.2 Switzerland.Interest.Rate CHF.DIn.10 Switzerland.Interest.Rate.5 CHF.tr.7 CHF.DIn.2
CAD	CAD.Close	CAD.RSI CAD.RSI.2 CAD.pctB.4 CAD.pctB CAD.pctR.1

Note: The number represents the previous lagged value. For example, GBP.RSI means previous 1 hour's RSI value for GBP, while GBP.RSI.2 means previous 3 hours' RSI value for GBP. The same applies for the others.

Table 15

Parameters' range for SVR

Parameter	Cost	Gamma	Epsilon
Min	0.001	0.001	0.01
Max	100	2	1

Table 16

Parameters' value for each SVR

FX	Parameters	Cost	Gamma	Epsilon
EUR	Short-run	53.00464	1.601857	0.01038708
	Long-run	1.00629539	0.09251582	0.10506435
GBP	Short-run	34.64943963	0.07398157	0.01858739
	Long-run	0.9999625	0.1000268	0.0999542
JPY	Short-run	76.2712586	0.001	0.02137905
	Long-run	0.9999935	0.1000327	0.1000083
AUD	Short-run	45.40515341	0.3097723	0.01208046
	Long-run	0.9993054	0.100317	0.0997352
CHF	Short-run	43.64658734	0.66690844	0.01776735
	Long-run	0.99994602	0.10011018	0.09992724
CAD	Short-run	49.24227534	0.11621762	0.01025506
	Long-run	0.99691798	0.09896066	0.09666125

Table 17

SVR model accuracy on FX

FX	Category	MAE	MSE	RMSE	RMSLE	MAPE	DS
EUR	Short-run	0.000973823	1.8965E-06	0.001377134	0.001377134	0.000873099	
	Long-run	0.001480847	3.68458E-06	0.001919525	0.001919525	2.011513	
	Final	0.000891139	1.94472E-06	0.001394531	0.001394531	0.000799461	47.78412
GBP	Short-run	0.02966153	0.002297687	0.04793419	0.04793419	0.02245175	
	Long-run	0.002018383	8.05889E-06	0.002838819	0.002838819	1.497722	
	Final	0.029686	0.002300608	0.04796466	0.04796466	0.0224716	50.13164
JPY	Short-run	0.1200817	0.02817879	0.1678654	0.1678654	0.00110681	
	Long-run	0.16273	0.04373496	0.209129	0.209129	8.115387	
	Final	0.1158848	0.03083311	0.1755936	0.1755936	0.001067389	47.91575
AUD	Short-run	0.00093851	1.53673E-06	0.001239651	0.001239651	0.001268291	
	Long-run	0.001487588	3.53298E-06	0.001879621	0.001879621	1.826324	
	Final	0.000900495	1.61798E-06	0.001271997	0.001271997	0.001217807	47.01624
CHF	Short-run	0.001009471	1.74311E-06	0.001320267	0.001320267	0.001029494	
	Long-run	0.001870985	5.49804E-06	0.00234479	0.00234479	1.35891	
	Final	0.000789145	1.35647E-06	0.001164676	0.001164676	0.000804478	46.68714
CAD	Short-run	0.001295006	3.01717E-06	0.001736999	0.001736999	0.000977445	
	Long-run	0.001825474	5.33341E-06	0.002309417	0.002309417	8.992123	
	Final	0.001233049	3.19183E-06	0.001786571	0.001786571	0.00092953	47.80606

Note: “Final” means the final prediction.

Table 18

Parameters' range for deep learning model

Parameter	Category	Description
Activation	Long-run	Rectifier or RectifierWithDropout
	Short-run	Rectifier or RectifierWithDropout
	Long-run Full	Rectifier or RectifierWithDropout
	Short-run Full	Rectifier or RectifierWithDropout
Layers	Long-run	1
	Short-run	2 to 10
	Long-run Full	2 to 10
	Short-run Full	2 to 10
Neurons in Each Layer	Long-run	10 to 100
	Short-run	10 to 100
	Long-run Full	10 to 100
	Short-run Full	10 to 100
Epochs	Long-run	0.1 to 10000
	Short-run	0.1 to 10000
	Long-run Full	0.1 to 10000
	Short-run Full	0.1 to 10000
Input Dropout Ratio	Long-run	0 to 0.3
	Short-run	0 to 0.3
	Long-run Full	0 to 0.3
	Short-run Full	0 to 0.3
L1 Regularization	Long-run	0 to 0.001
	Short-run	0 to 0.001
	Long-run Full	0 to 0.001
	Short-run Full	0 to 0.001
L2 Regularization	Long-run	0 to 0.001
	Short-run	0 to 0.001
	Long-run Full	0 to 0.001
	Short-run Full	0 to 0.001

Note: "Short-run Full" means the short-run data without MARS feature selection. Same applies for "Long-run Full".

Table 19

Parameters' optimal value for deep learning models of each FX

FX	Category	Epochs	Activation	Hidden	L1	L2	Input_dropout_ratio
EUR	Long-run	3088.7	Rectifier	100	0.00036	0.00004	0
	Short-run	4181	RectifierWithDropout	83 82	0.00042	0.00027	0.2
	Long-run Full	6497.6	Rectifier	18 90 54 19 59 38 42 41	0.0001	0	0
	Short-run Full	4181	RectifierWithDropout	83 82	0.00042	0.00027	0.2
GBP	Long-run	9448.1	RectifierWithDropout	80	0.00018	0.00027	0.15
	Short-run	9570.9	Rectifier	30 26	0.00026	0.00002	0.25
	Long-run Full	7677	Rectifier	85 48 22 31	0.00023	0.00017	0.05
	Short-run Full	9444.7	Rectifier	20 75 100 98	0.00093	0.0005	0.05
JPY	Long-run	9152	Rectifier	30	0.00002	0.00007	0.1
	Short-run	2944.4	Rectifier	61 17 34 39 69	0.00003	0.00097	0.1
	Long-run Full	2810.7	Rectifier	63 72	0.00004	0.00008	0
	Short-run Full	2395.6	Rectifier	52 11 33	0.00077	0.00006	0.1
AUD	Long-run	5251.5	Rectifier	10	0.0001	0.00001	0
	Short-run	6800.2	Rectifier	20 38 41 68 32 52	0.00015	0.00069	0.1
	Long-run Full	7677	Rectifier	85 48 22 31	0.00023	0.00017	0.05
	Short-run Full	2395.6	Rectifier	52 11 33	0.00077	0.00006	0.1
CHF	Long-run	2760.6	Rectifier	50	0.00032	0.00054	0.05
	Short-run	2751.9	Rectifier	30 26	0.00027	0.00041	0.05
	Long-run Full	9682.2	Rectifier	19 26 32 58 43 46 12 52	0.00001	0.00067	0
	Short-run Full	5429.1	RectifierWithDropout	66 15	0.00021	0.00069	0.05
CAD	Long-run	7468.8	Rectifier	40	0.0003	0.00041	0.3
	Short-run	340.5	Rectifier	90 86 93 93	0.00005	0.00002	0
	Long-run Full	4732.6	Rectifier	50	0.00035	0.00024	0.1
	Short-run Full	745	Rectifier	70 99 81 73	0.00044	0.00032	0

Table 20

Deep learning model (with MARS) accuracy on FX

FX	Category	MAE	MSE	RMSE	RMSLE	MAPE	DS
EUR	Short-run	0.000971694	1.88922E-06	0.001374487	0.000650054		
	Long-run	0.001475775	3.64078E-06	0.001908082	0.001908493		
	Final	0.000812646	1.68895E-06	0.001299595	0.001299595	0.000733493	47.87187
GBP	Short-run	0.001510875	6.23582E-06	0.002497162	0.001039129		
	Long-run	0.002009889	7.68721E-06	0.002772581	0.002772311		
	Final	0.001456503	6.3017E-06	0.002510319	0.002510319	0.001023819	48.06933
JPY	Short-run	0.1200761	0.02818367	0.1678799	0.001536384		
	Long-run	0.1622357	0.04321555	0.2078835	0.2078947		
	Final	0.1201002	0.03180625	0.1783431	0.1783431	0.001006383	47.98157
AUD	Short-run	0.000939312	1.54171E-06	0.001241655	0.000713326		
	Long-run	0.001486561	3.52652E-06	0.001877902	0.001877965		
	Final	0.000892851	1.59665E-06	0.001263585	0.001263585	0.001207409	46.75296
CHF	Short-run	0.001006482	1.74063E-06	0.001319329	0.000665852		
	Long-run	0.001866881	5.47794E-06	0.0023405	0.002340597		
	Final	0.00077901	1.32874E-06	0.001152709	0.001152709	0.000794184	46.8846
CAD	Short-run	0.001420949	3.62107E-06	0.001902911	0.000812978		
	Long-run	0.001820183	5.31893E-06	0.002306281	0.002306481		
	Final	0.001167721	3.00002E-06	0.001725662	0.001725662	0.000842341	48.02545

Table 21

Deep learning model (without MARS) accuracy on FX

FX	Category	MAE	MSE	RMSE	RMSLE	MAPE	DS
EUR	Short-run	0.001403717	3.35565E-06	0.001831844	0.000866806		
	Long-run	0.001475775	3.64078E-06	0.001908082	0.001908493		
	Final	0.001345499	3.42056E-06	0.001849475	0.001849475	0.001207127	46.95042
GBP	Short-run	0.002147126	1.31428E-05	0.003625303	0.001506392		
	Long-run	0.002019657	7.96293E-06	0.002821866	0.002824093		
	Final	0.002218788	1.64641E-05	0.004057594	0.004057594	0.001592861	47.69636
JPY	Short-run	0.2868514	0.1765537	0.420183	0.003619385		
	Long-run	0.1620152	0.0433705	0.2082558	0.2082558		
	Final	0.2944247	0.1870553	0.4324989	0.4324989	0.002624989	48.74945
AUD	Short-run	0.003870271	2.2417E-05	0.00473466	0.002717732		
	Long-run	0.001488281	3.54591E-06	0.001883058	0.001883051		
	Final	0.004579032	3.26056E-05	0.00571013	0.00571013	0.006251149	47.52084
CHF	Short-run	0.001355293	2.97555E-06	0.001724979	0.000871212		
	Long-run	0.001875798	5.52241E-06	0.002349981	0.002350179		
	Final	0.001267102	2.86064E-06	0.001691343	0.001691343	0.001293115	47.52084
CAD	Short-run	0.001939748	4.98573E-06	0.002360449	0.001003445		
	Long-run	0.002204758	6.78934E-06	0.002902452	0.002823545		
	Final	0.001907584	4.87892E-06	0.002338594	0.002334956	0.001394753	47.95034

Table 22

Base model accuracy on FX (best model in terms of smallest MAE highlighted in yellow)

FX	Category	MAE	MSE	RMSE	RMSLE	MAPE	DS
EUR	RW	0.000816627	1.6894E-06	0.001302053	0.001302053	0.000734707	47.30145
	ARIMA(0,1,0)	0.000816991	1.68982E-06	0.001302216	0.001302216	0.000735036	47.41115
	GARCH(0,5)	0.000882987	2.15793E-06	0.00146899	0.00146899	0.000792036	46.89216
GBP	RW	0.001462437	6.39904E-06	0.002689788	0.002689788	0.001036317	48.06933
	ARIMA(2,1,2)	0.001461959	6.33109E-06	0.002696215	0.002696215	0.001030401	48.11321
	GARCH(0,4)	0.001462536	6.42566E-06	0.002725006	0.002725006	0.001036725	47.58454
JPY	RW	0.1206863	0.03239593	0.1794524	0.1794524	0.001029049	47.54278
	ARIMA(5,2,0)	0.1225145	0.04447095	0.1956635	0.1956635	0.001128171	47.7183
	GARCH(0,5)	0.3339736	0.1475481	0.3841199	0.3841199	0.003037175	47.61696
AUD	RW	0.000917219	1.72595E-06	0.001394132	0.001394132	0.001225486	46.42387
	ARIMA(0,1,1)	0.000916269	1.72567E-06	0.001394012	0.001394012	0.001224205	46.42387
	GARCH(0,1)	0.000917224	1.72599E-06	0.001394147	0.001394147	0.001225486	46.43406
CHF	RW	0.000818028	1.37995E-06	0.001286255	0.001286255	0.000871984	46.18254
	ARIMA(0,1,2)	0.000820924	1.38525E-06	0.00128869	0.00128869	0.000874937	46.55551
	GARCH(5,3)	0.000880539	1.71012E-06	0.001307716	0.001307716	0.000897432	46.43092
CAD	RW	0.001171235	3.00895E-06	0.001734634	0.001734634	0.000883324	47.69636
	ARIMA(5,2,0)	0.001297292	3.48681E-06	0.001867299	0.001867299	0.00097855	48.4423
	GARCH(0,5)	0.001304776	3.75464E-06	0.001937688	0.001937688	0.000983806	47.02394

Table 23

Independent variables selected from MARS for each FX return subset

FX	Long-run	Short-run
EUR	EUR.Close	EUR.RSI EUR.macd EUR.DIn CHF.pctB GBP.tr US.Unemployment.Rate EUR.macd.signal Switzerland.CESI NSX.Low NSX.trueLow
GBP	GBP.Close	GBP.macd GBP.macd.1 GBP.tr.5 GBP.tr.2 US.New.Home.Sales.7 GBP.macd.signal.6 GBP.atr Eurozone.CESI.3 GBP.tr BCO.pctR.2 GBP.pctB.5 GBP.DIn UK.Industrial.Production.MoM GBP.DX GBP.RSI GBP.RSI.2
JPY	JPY.Close	JPY.RSI JPY.RSI.1 Canada.PMI.3 JPY.RSI.2 GBP.tr US.Nonfarm.Payroll JPY.macd JPY.DIp.4 Switzerland.CPI.MoM.3 JPY.aroonDown.3
AUD	AUD.Close	AUD.RSI AUD.RSI.2 JPY.aroonDown.8 AUD.RSI.4 Australia.Unemployment.Rate.4

		AUD.pctB
		AUD.pctR.1
		AUD.tr.1
		Japan.CESI.1
		US.Trade.Balance.6
CHF	CHF.Close	CHF.DIn
		CHF.Din.2
		CHF.RSI
		Switzerland.Interest.Rate
		US.PPI.YoY.7
		Switzerland.Interest.Rate.5
		CHF.DIn.10
		CHF.tr.7
		CHF.DIp.5
		CHF.SMI.7
		Eurozone.CESI.3
CAD	CAD.Close	CAD.CloseShort
		CAD.RSI
		CAD.RSI.2
		CAD.DIp.1
		CAD.pctB
		CAD.DIp
		US.Retail.Sales.MoM
		Switzerland.CESI.9
		US.Trade.Balance
		CHF.DX.10
		CHF.RSI.8

Table 24

Independent variables selected from MARS for each FX volatility subset

FX	Long-run	Short-run
EUR	EUR.Close	EUR.pctB
		EUR.RSI
		EUR.SMI
		EUR.SMI.Signal
		CHF.pctB
		EUR.aroonDown
		GBP.pctR
		CHF.Low
		GBP.tr
		EUR.pctR
GBP	GBP.Close	GBP.tr
		GBP.tr.5
		GBP.RSI
		GBP.RSI.2
		GBP.tr.2
		Eurozone.EONIA.6
		GBP.DIn
		GBP.CV.7
		GBP.pctB
		GBP.pctB.2
JPY	JPY.Close	JPY.RSI.2
		JPY.Open
		JPY.Close
		JPY.High.4
		JPY.RSI
		Eurozone.ZEW.Survey
		JPY.RSI.4
		Japan.Interest.Rate
		GBP.tr
		GBP.tr.4
AUD	AUD.Close	AUD.pctB
		AUD.pctB.1
		AUD.RSI
		AUD.RSI.4
		AUD.tr.8
		WTI.RSI.10
		AUD.pctR.8
		JPY.RSI.3
		WTI.atr
		AUD.RSI.2

CHF	CHF.Close	CHF.DIn CHF.High CHF.Low CHF.Close CHF.Open.1 US.PPI.YoY.1 US.PPI.MoM.7 Switzerland.Interest.Rate CHF.CV.1 Eurozone.Interest.Rate CHF.DIn.3
CAD	CAD.Close	CAD.RSI CAD.RSI.2 CHF.pctB CAD.RSI.1 CAD.DIp CAD.BBands.BPosition.3 Japan.Interest.Rate.8 CAD.pctR.3 CAD.DIp.4 Japan.Trade.Balance.6 Switzerland.CPI.YoY.1

Table 25

Independent variables selected from MARS for each FX RSI subset

FX	Long-run	Short-run
EUR	EUR.Close	EUR.RSI EUR.SMI GBP.tr EUR.SMI.Signal CHF.pctB EUR.pctB EUR.macd CHF.RSI EUR.macd.signal US.Nonfarm.Payroll Eurozone.Retail.Sales.MoM EUR.pctR EUR.DIn
GBP	GBP.Close	GBP.BBands.MAPosition GBP.tr.2 GBP.macd GBP.macd.1 GBP.tr.1 GBP.RSI.2 GBP.macd.6 GBP.tr GBP.RSI.3
JPY	JPY.Close	JPY.macd JPY.macd.1 JPY.BBands.MAPosition GBP.atr JPY.RSI.2 JPY.macd.4 JPY.SMI.Strength.1 Eurozone.ZEW.Survey JPY.pctB JPY.atr.1 GBP.tr
AUD	AUD.Close	AUD.macd AUD.macd.1 AUD.macd.7 AUD.RSI AUD.BBands.BPosition.1 WTI.DX.4 WTI.tr.3 WTI.tr.6

		AUD.CV.7 AUD.BBands.MAPosition AUD.RSI.2 WTI.DX.5 WTI.tr.9
CHF	CHF.Close	CHF.DIn CHF.BBands.MAPosition Switzerland.Interest.Rate CHF.macd.8 CHF.RSI.3 Switzerland.Interest.Rate.4 CAD.ADX.6 CHF.DIn.2 EUR.DIp Switzerland.CPI.MoM.1 WTI.DIp.9 AUX.RSI.6 CHF.pctB US.Nonfarm.Payroll EUR.DIn.1
CAD	CAD.Close	CAD.BBands.MAPosition CAD.DIn CAD.pctB Canada.CESI.10 CHF.tr.1 Canada.Current.Account.1 JPY.aroonUp.2 JPY.pctR.2 JPY.aroonUp CAD.pctB.1 CAD.aroonDown.8

Table 26

Parameters' optimal value for deep learning models of each FX return subset

FX	Category	Epochs	Activation	Hidden	L1	L2	Input_dropout_ratio
EUR	Long-run	7677	Rectifier	50	0.00023	0.00017	0.05
	Short-run	8155.5	RectifierWithDropout	59 61 32	0.00098	0.00004	0.1
GBP	Long-run	246.3	RectifierWithDropout	100	0.00001	0.00005	0.1
	Short-run	4114.9	Rectifier	42 61 61 50 48 62 71 77 62	0.00039	0.00057	0.1
JPY	Long-run	6101.3	RectifierWithDropout	60	0.00013	0.00074	0.15
	Short-run	7265.8	Rectifier	99 22 84 88 13 63 50 18	0.00025	0.00001	0.25
AUD	Long-run	6101.3	RectifierWithDropout	60	0.00013	0.00074	0.15
	Short-run	569.9	Rectifier	34 74 13 48 48 75 25 11	0.0007	0.00092	0.1
CHF	Long-run	9682.2	Rectifier	10	0.00001	0.00067	0
	Short-run	1905.2	Rectifier	52 96	0.00074	0.00067	0.3
CAD	Long-run	4415	Rectifier	30	0.00046	0.00008	0.1
	Short-run	7651.5	Rectifier	43 46 12 52 89 41	0.00066	0.00095	0.05

Table 27

Parameters' optimal value for deep learning models of each FX volatility subset

FX	Category	Epochs	Activation	Hidden	L1	L2	Input_dropout_ratio
EUR	Long-run	9800.6	Rectifier	10	0.00084	0.00025	0
	Short-run	2957.4	Rectifier	30 73 42 10 21 78	0.00081	0.00064	0.2
GBP	Long-run	4544.4	Rectifier	100	0.00015	0.00003	0
	Short-run	3321	Rectifier	77 99 69 77 88 43	0.00094	0.00049	0.2
JPY	Long-run	6497.6	Rectifier	80	0.0001	0	0
	Short-run	2541.5	RectifierWithDropout	25 14 82 88	0.00073	0.00083	0
AUD	Long-run	9025	Rectifier	50	0.00057	0.00065	0.05
	Short-run	6199.2	Rectifier	71 41 42 90 29 28	0.00076	0.00074	0.3
CHF	Long-run	9025	Rectifier	50	0.00057	0.00065	0.05
	Short-run	4633.4	Rectifier	24 51 65 20 95 11	0.00021	0.00094	0
CAD	Long-run	7693.7	Rectifier	90	0.00006	0.00069	0.3
	Short-run	6233.8	Rectifier	18 59 39 20 87 59 17 24 28	0.00077	0.00078	0.1

Table 28

Parameters' optimal value for deep learning models of each FX RSI subset

FX	Category	Epochs	Activation	Hidden	L1	L2	Input_dropout_ratio
EUR	Long-run	7552.2	Rectifier	40	0.00002	0.00016	0.05
	Short-run	2434.8	RectifierWithDropout	75 77	0.00064	0.00045	0.05
GBP	Long-run	3172.8	Rectifier	80	0.00093	0.00005	0
	Short-run	1439.1	Rectifier	64 63 96 36 74 41	0.0006	0.00066	0.15
JPY	Long-run	3812.7	Rectifier	80	0.00014	0.00006	0
	Short-run	8141.3	RectifierWithDropout	54 77	0.00081	0.00041	0.15
AUD	Long-run	7568.7	Rectifier	100	0.00098	0.00009	0.05
	Short-run	2541.5	RectifierWithDropout	39 69 27	0.00073	0.00083	0
CHF	Long-run	5788.2	RectifierWithDropout	50	0.00051	0.00094	0.15
	Short-run	569.9	Rectifier	64 83 65 92 89 90 92 50	0.0007	0.00092	0.1
CAD	Long-run	6305.7	Rectifier	80	0.00069	0.00078	0.05
	Short-run	6510.4	Rectifier	37 60 45 60 95 36 42 45	0.00021	0.00002	0.15

Table 29

Deep learning model accuracy on FX return subset

FX	Category	MAE	MSE	RMSE	RMSLE	MAPE	DS
EUR	Short-run	0.002430279	1.01717E-05	0.003189309	0.001509902		
	Long-run	0.002188888	9.27663E-06	0.003045755	0.003047757		
	Final	0.00363111	2.04123E-05	0.004517998	0.004517998	0.003263135	58.45588
GBP	Short-run	0.003216366	2.89601E-05	0.005381459	0.002234661		
	Long-run	0.003015239	2.41903E-05	0.004918358	0.004937322		
	Final	0.00476143	4.69738E-05	0.00685374	0.00685374	0.003433682	56.41476
JPY	Short-run	0.2312591	0.09775993	0.3126658	0.002869016		
	Long-run	0.2085287	0.0755403	0.274846	0.274846		
	Final	0.3530584	0.2034524	0.451057	0.451057	0.003252038	60.07067
AUD	Short-run	0.001571106	3.91023E-06	0.001977431	0.001137286		
	Long-run	0.001720503	4.83224E-06	0.002198237	0.002198561		
	Final	0.002657912	1.10985E-05	0.003331436	0.003331436	0.003614067	58.97833
CHF	Short-run	0.00190003	5.77913E-06	0.002403982	0.001211156		
	Long-run	0.002136958	7.36407E-06	0.002713682	0.002714208		
	Final	0.003182952	1.51711E-05	0.003895009	0.003895009	0.003239517	58.24916
CAD	Short-run	0.002960307	1.43071E-05	0.003782465	0.001617625		
	Long-run	0.002380623	8.72119E-06	0.002953167	0.00295497		
	Final	0.004253416	2.70529E-05	0.005201239	0.005201239	0.003188096	57.78781

Table 30

Base model accuracy on FX return subset (best model in terms of smallest MAE highlighted in yellow)

FX	Category	MAE	MSE	RMSE	RMSLE	MAPE	DS
EUR	RW	0.004233463	3.04662E-05	0.00551962	0.00551962	0.003802256	52.57353
	ARIMA(1,1,0)	0.004236592	3.06088E-05	0.005532521	0.005532521	0.003805028	52.20588
	GARCH(0,4)	0.004431114	3.4429E-05	0.005867622	0.005867622	0.003977895	48.50746
GBP	RW	0.005399958	5.68479E-05	0.007539757	0.007539757	0.003895228	50.43937
	ARIMA(0,1,1)	0.005414138	5.71354E-05	0.007558798	0.007558798	0.00390612	49.73638
	GARCH(0,4)	0.006306727	7.84629E-05	0.008857929	0.008857929	0.004572164	51.15044
JPY	RW	0.4257784	0.2938106	0.542043	0.542043	0.003927616	50.88339
	ARIMA(3,1,1)	0.4264577	0.2941731	0.5423773	0.5423773	0.003936776	51.94346
	GARCH(0,5)	0.5238964	0.4437077	0.6661139	0.6661139	0.004852073	52.22816
AUD	RW	0.003092073	1.52076E-05	0.003899692	0.003899692	0.004198254	45.51084
	ARIMA(0,1,1)	0.003054703	1.46436E-05	0.003826699	0.003826699	0.004147048	43.96285
	GARCH(5,3)	0.003196304	1.99398E-05	0.004465395	0.004465395	0.004342647	45.24181
CHF	RW	0.004166708	2.72167E-05	0.005216959	0.005216959	0.004245887	46.80135
	ARIMA(2,1,4)	0.004148149	2.65606E-05	0.005153694	0.005153694	0.004228081	46.80135
	GARCH(0,4)	0.004286613	2.79565E-05	0.005287389	0.005287389	0.00437135	45.73379
CAD	RW	0.005000721	3.72579E-05	0.006103921	0.006103921	0.003759566	47.40406
	ARIMA(0,1,1)	0.005003544	3.75522E-05	0.006127988	0.006127988	0.003762094	49.88713
	GARCH(0,4)	0.00598082	5.54192E-05	0.007444408	0.007444408	0.004503912	46.24146

Table 31

Deep learning model accuracy on FX volatility subset

FX	Category	MAE	MSE	RMSE	RMSLE	MAPE	DS
EUR	Short-run	0.001981415	9.77131E-06	0.00312591	0.001481914		
	Long-run	0.001970836	9.78013E-06	0.00312732	0.003132929		
	Final	0.002648526	1.57836E-05	0.003972862	0.003972862	0.002392274	54.85437
GBP	Short-run	0.002139243	1.61479E-05	0.004018446	0.001671115		
	Long-run	0.002402834	1.53066E-05	0.003912368	0.003919464		
	Final	0.002985296	2.30208E-05	0.004797997	0.004797997	0.002165355	52.87865
JPY	Short-run	0.1878381	0.08217039	0.2866538	0.002658826		
	Long-run	0.2024937	0.07795815	0.2792099	0.2792099		
	Final	0.2651331	0.1496833	0.3868892	0.3868892	0.002456156	48.32347
AUD	Short-run	0.00128939	3.13877E-06	0.001771657	0.001021459		
	Long-run	0.001571434	4.30487E-06	0.002074818	0.002075442		
	Final	0.002094175	8.00533E-06	0.002829369	0.002829369	0.002867024	50.95785
CHF	Short-run	0.001489597	4.82405E-06	0.002196371	0.001102331		
	Long-run	0.002230299	7.88997E-06	0.002808909	0.002808752		
	Final	0.002680479	1.31156E-05	0.003621541	0.003621541	0.002706142	57.74648
CAD	Short-run	0.003578405	1.76855E-05	0.004205409	0.001813208		
	Long-run	0.001931064	6.09723E-06	0.002469258	0.0024694		
	Final	0.004038609	2.44689E-05	0.004946601	0.004946601	0.003022026	52.40223

Table 32

Base model accuracy on FX volatility subset (best model in terms of smallest MAE highlighted in yellow)

FX	Category	MAE	MSE	RMSE	RMSLE	MAPE	DS
EUR	RW	0.003013683	2.60729E-05	0.005106161	0.005106161	0.002722015	41.74757
	ARIMA(0,1,0)	0.003011315	0.000026135	0.00511224	0.00511224	0.002719827	41.74757
	GARCH(0,4)	0.003077475	2.78616E-05	0.005278407	0.005278407	0.002778475	42.57426
GBP	RW	0.003751758	4.18154E-05	0.006466481	0.006466481	0.002713484	37.64393
	ARIMA(0,1,1)	0.003571516	3.41194E-05	0.005841177	0.005841177	0.002584357	37.02391
	GARCH(0,5)	0.006335711	7.04001E-05	0.008390475	0.008390475	0.004644752	37.45552
JPY	RW	0.3368044	0.3475254	0.5895128	0.5895128	0.003104814	38.46154
	ARIMA(0,1,1)	0.3199391	0.3015596	0.5491444	0.5491444	0.002955915	39.25049
	GARCH(5,1)	0.3858795	0.3998652	0.632349	0.632349	0.003531678	38.84462
AUD	RW	0.002640655	1.51989E-05	0.003898582	0.003898582	0.003616462	37.73946
	ARIMA(0,1,1)	0.002544737	1.46868E-05	0.003832339	0.003832339	0.003484758	37.93103
	GARCH(5,3)	0.003285903	4.2503E-05	0.006519429	0.006519429	0.004499486	42.94004
CHF	RW	0.003523081	2.2366E-05	0.004729268	0.004729268	0.003558156	35.21127
	ARIMA(1,1,1)	0.003345322	2.02095E-05	0.004495494	0.004495494	0.003380407	30.28169
	GARCH(5,3)	0.003194679	1.84016E-05	0.004289707	0.004289707	0.003233478	30.65693
CAD	RW	0.00317777	2.03758E-05	0.004513953	0.004513953	0.002360353	37.09497
	ARIMA(0,1,1)	0.00304599	1.90607E-05	0.004365856	0.004365856	0.002263108	36.75978
	GARCH(0,5)	0.003322833	2.30397E-05	0.004799963	0.004799963	0.002468667	41.01124

Table 33

Deep learning model accuracy on FX RSI subset

FX	Category	MAE	MSE	RMSE	RMSLE	MAPE	DS
EUR	Short-run	0.001182867	2.98332E-06	0.001727229	0.000815892		
	Long-run	0.001642972	4.78616E-06	0.002187728	0.002190722		
	Final	0.001913424	7.4445E-06	0.00272846	0.00272846	0.001713195	62.5
GBP	Short-run	0.002072186	1.62292E-05	0.004028542	0.001677259		
	Long-run	0.002230022	1.01537E-05	0.003186482	0.00318377		
	Final	0.002777665	2.12808E-05	0.004613112	0.004613112	0.001999343	67.12644
JPY	Short-run	0.1471386	0.05443389	0.2333107	0.002158811		
	Long-run	0.1708987	0.05009322	0.2238151	0.2238151		
	Final	0.2289388	0.1140999	0.3377868	0.3377868	0.002122039	62.78586
AUD	Short-run	0.001181194	2.7015E-06	0.001643623	0.000945151		
	Long-run	0.001496169	3.74879E-06	0.001936179	0.001936601		
	Final	0.001930362	6.92143E-06	0.002630861	0.002630861	0.002609956	66.93548
CHF	Short-run	0.001116661	2.40143E-06	0.001549655	0.00078271		
	Long-run	0.001990607	6.77623E-06	0.002603119	0.00260278		
	Final	0.002207762	8.55657E-06	0.002925161	0.002925161	0.002255435	61.37566
CAD	Short-run	0.00163873	5.05233E-06	0.00224774	0.000964092		
	Long-run	0.001953024	6.12649E-06	0.002475175	0.002475365		
	Final	0.002426744	1.09152E-05	0.003303817	0.003303817	0.001827588	71.10553

Table 34

Base model accuracy on FX RSI subset (best model in terms of smallest MAE highlighted in yellow)

FX	Category	MAE	MSE	RMSE	RMSLE	MAPE	DS
EUR	RW	0.003396158	2.27611E-05	0.004770857	0.004770857	0.003039941	41.5
	ARIMA(1,1,0)	0.003370147	2.22825E-05	0.00472043	0.00472043	0.003016429	41.5
	GARCH(5,1)	0.00343156	2.30274E-05	0.004798686	0.004798686	0.003072029	42.53165
GBP	RW	0.005339821	7.05152E-05	0.008397335	0.008397335	0.003832449	49.18794
	ARIMA(0,1,1)	0.005487914	7.45068E-05	0.00863173	0.00863173	0.003939503	46.43678
	GARCH(0,4)	0.005924955	8.55522E-05	0.009249441	0.009249441	0.004257934	49.18794
JPY	RW	0.3971502	0.3537662	0.5947825	0.5947825	0.003671354	46.15385
	ARIMA(1,1,1)	0.4040721	0.3555164	0.596252	0.596252	0.003733519	49.89605
	GARCH(0,5)	0.4847273	0.4569114	0.6759522	0.6759522	0.00447101	53.15126
AUD	RW	0.003517839	2.38959E-05	0.004888343	0.004888343	0.004758239	45.96774
	ARIMA(0,1,1)	0.00345739	2.28059E-05	0.004775551	0.004775551	0.004676537	46.77419
	GARCH(0,5)	0.003763027	2.43016E-05	0.004929666	0.004929666	0.005086953	47.68392
CHF	RW	0.003900837	2.70933E-05	0.005205124	0.005205124	0.003984311	40.74074
	ARIMA(1,1,0)	0.003814509	2.55549E-05	0.005055182	0.005055182	0.003896943	40.74074
	GARCH(0,5)	0.004039057	2.66685E-05	0.005164156	0.005164156	0.004125347	43.16354
CAD	RW	0.00477435	4.65139E-05	0.006820108	0.006820108	0.003593957	45.22613
	ARIMA(1,1,0)	0.004872043	4.63136E-05	0.00680541	0.00680541	0.003670745	48.24121
	GARCH(5,1)	0.005105154	5.96822E-05	0.007725423	0.007725423	0.003833657	46.31043

Figures

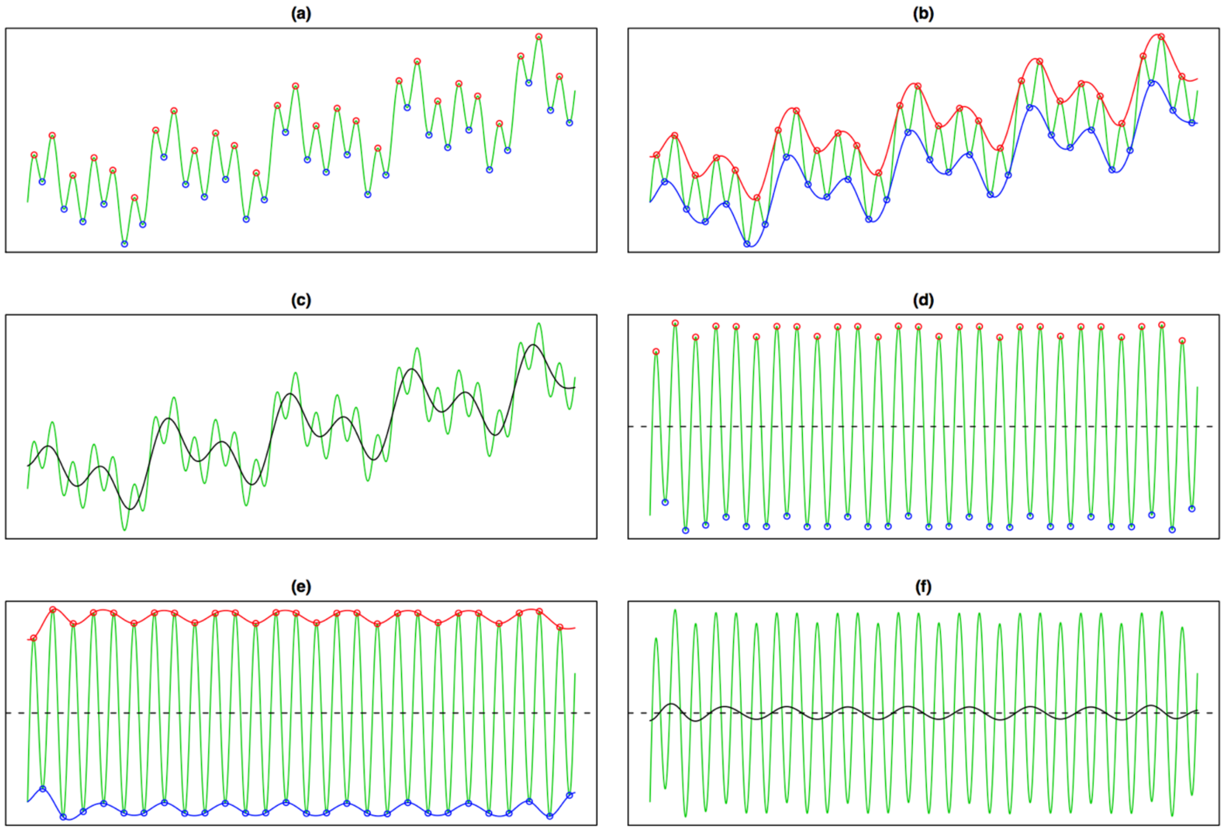

Figure 1. Sifting (Kim & Oh, 2009)

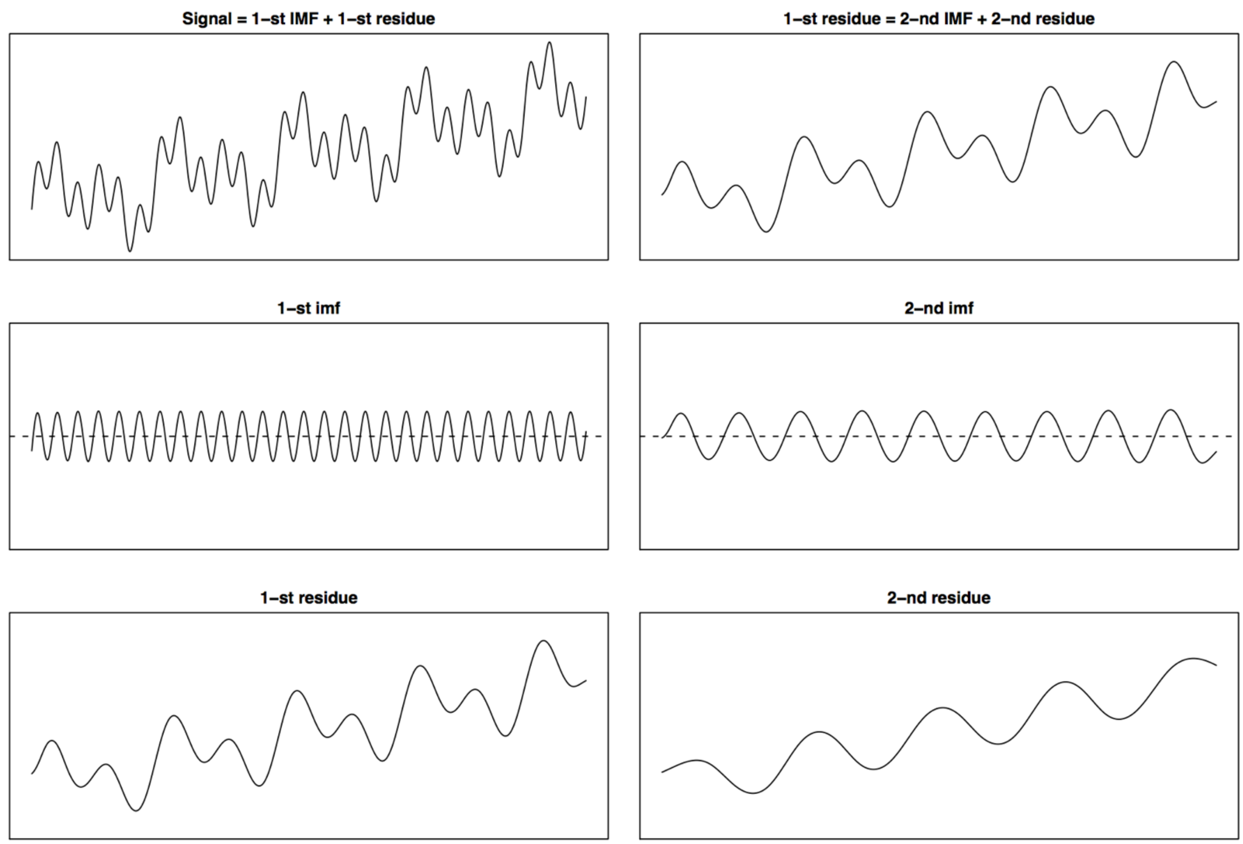

Figure 2. IMF_1 and IMF_2 by sifting (Kim & Oh, 2009)

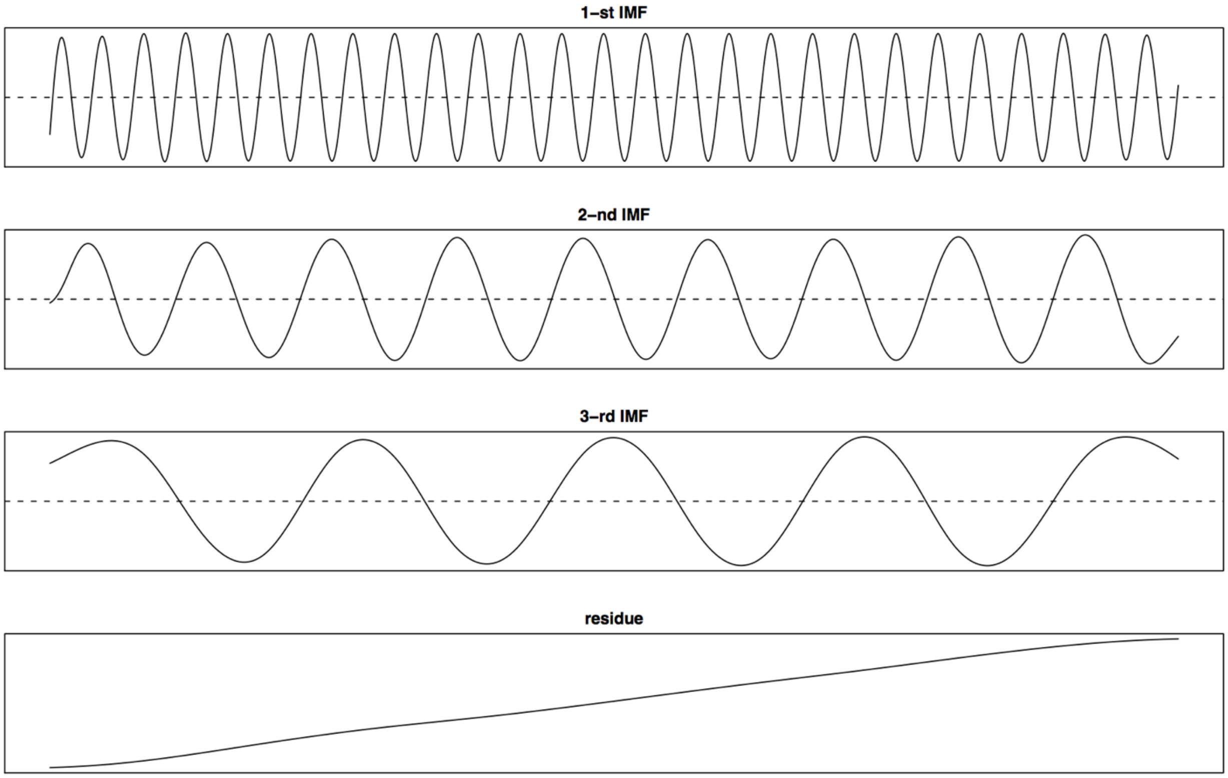

Figure 3. Example of final EMD decomposition of a data series (Kim & Oh, 2009)

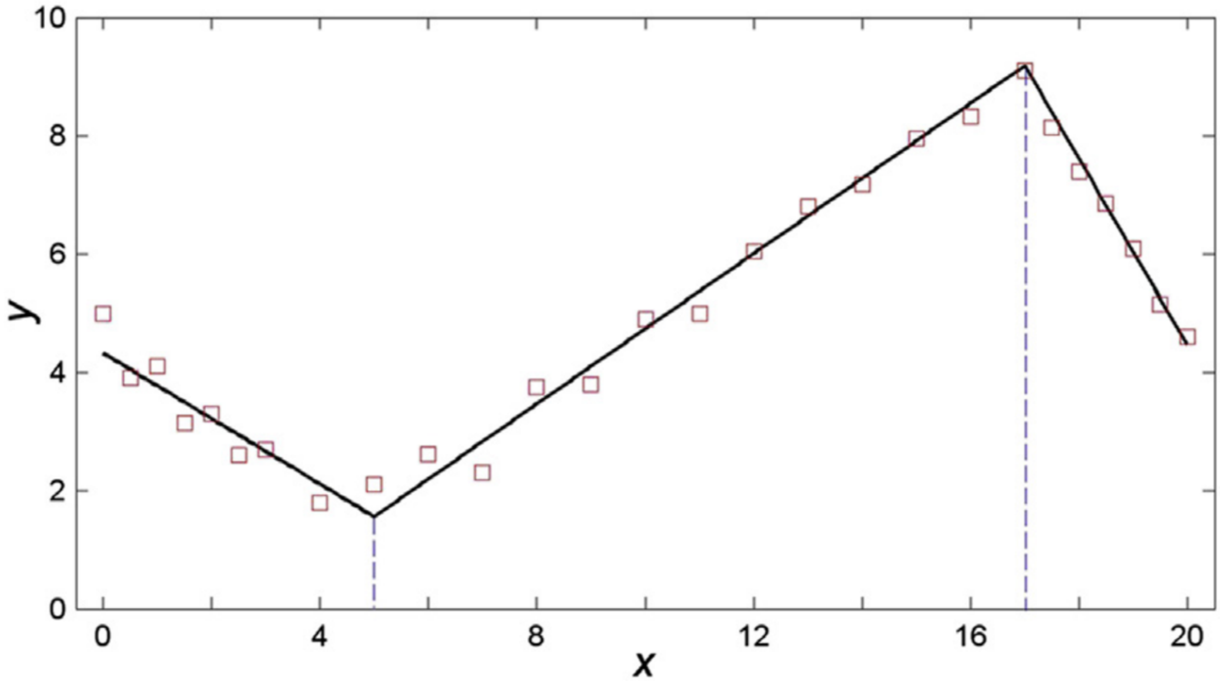

Figure 4. Example of MARS (Zhang & Goh, 2016)

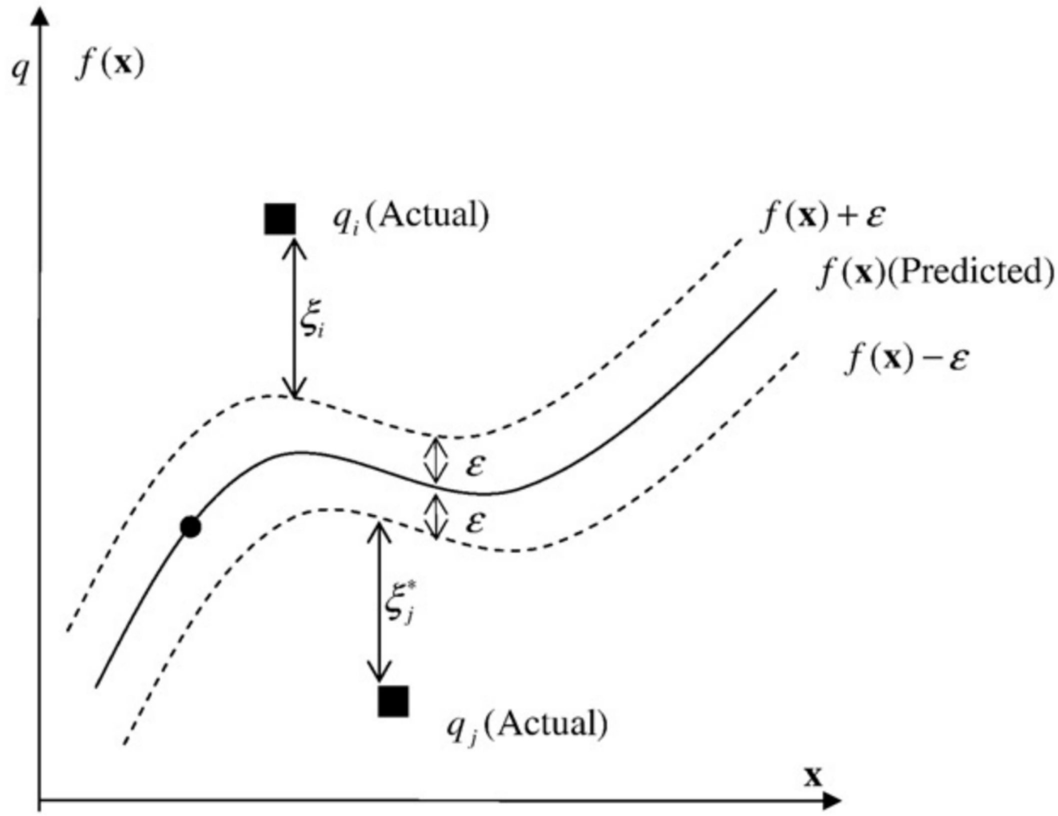

Figure 5. A schematic representation of SVR using ε-insensitive loss function (Lu *et al.*, 2009)

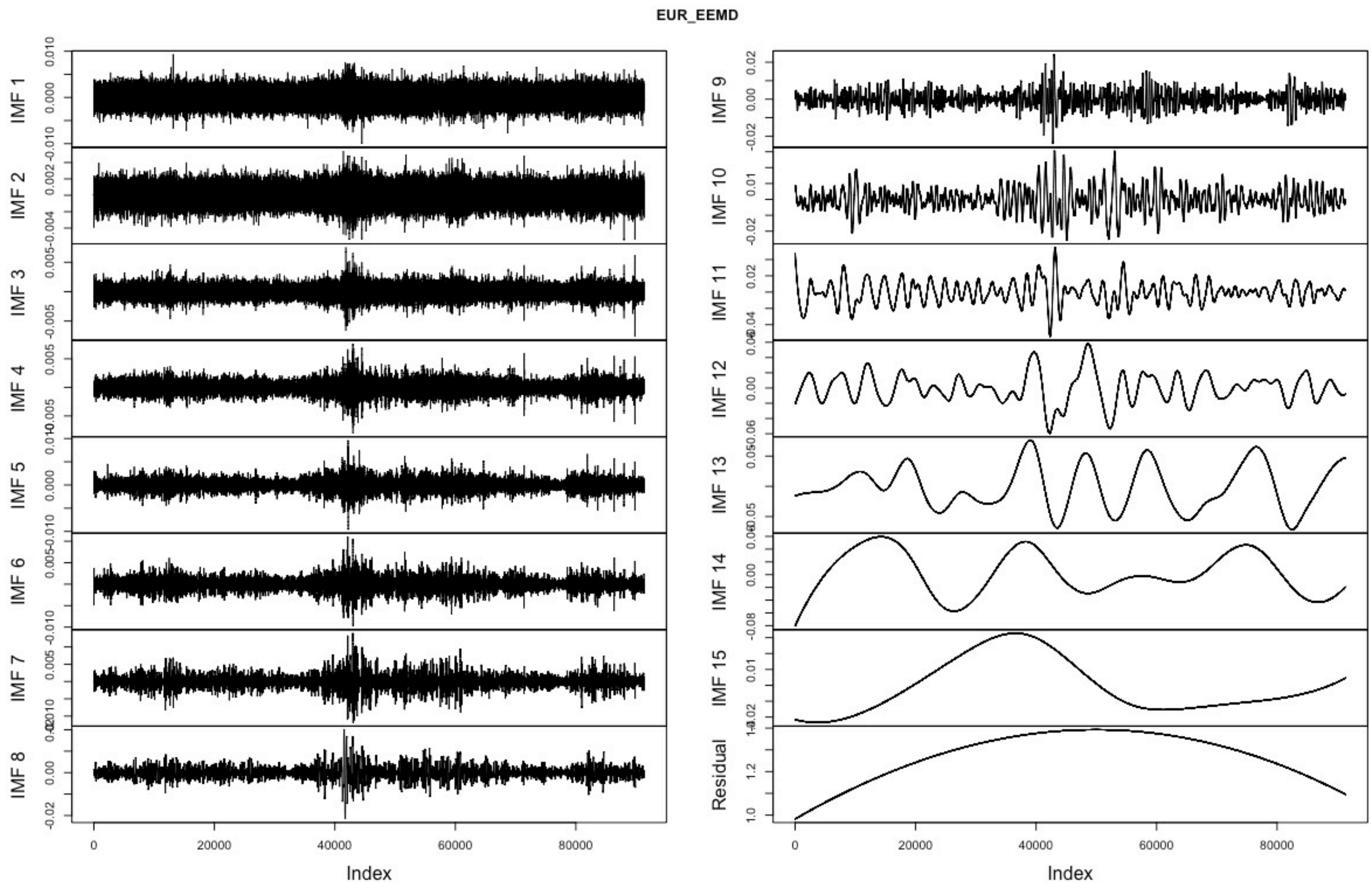

Figure 6. EEMD on hourly EUR/USD closing prices

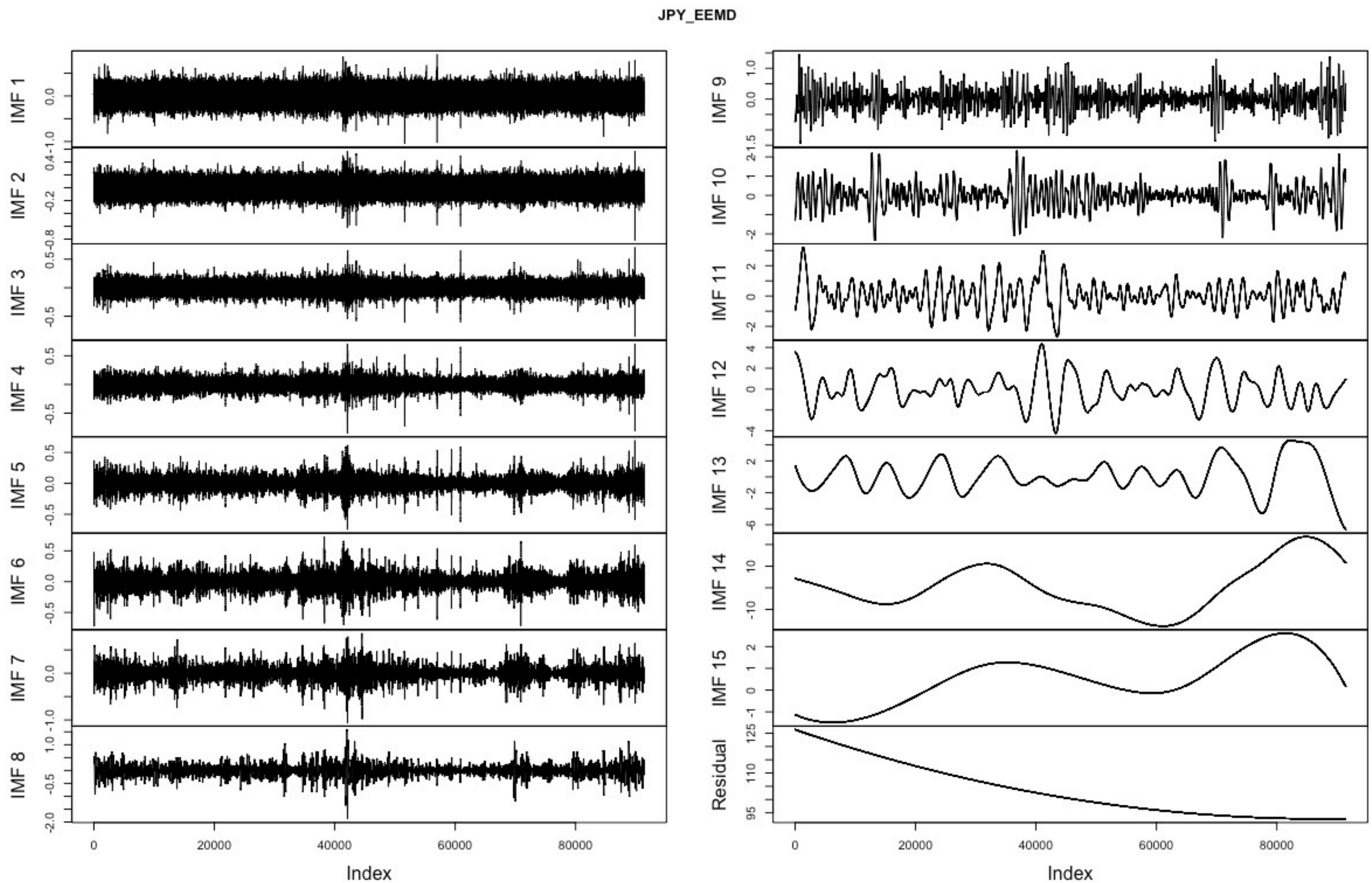

Figure 7. EEMD on hourly USD/JPY closing prices

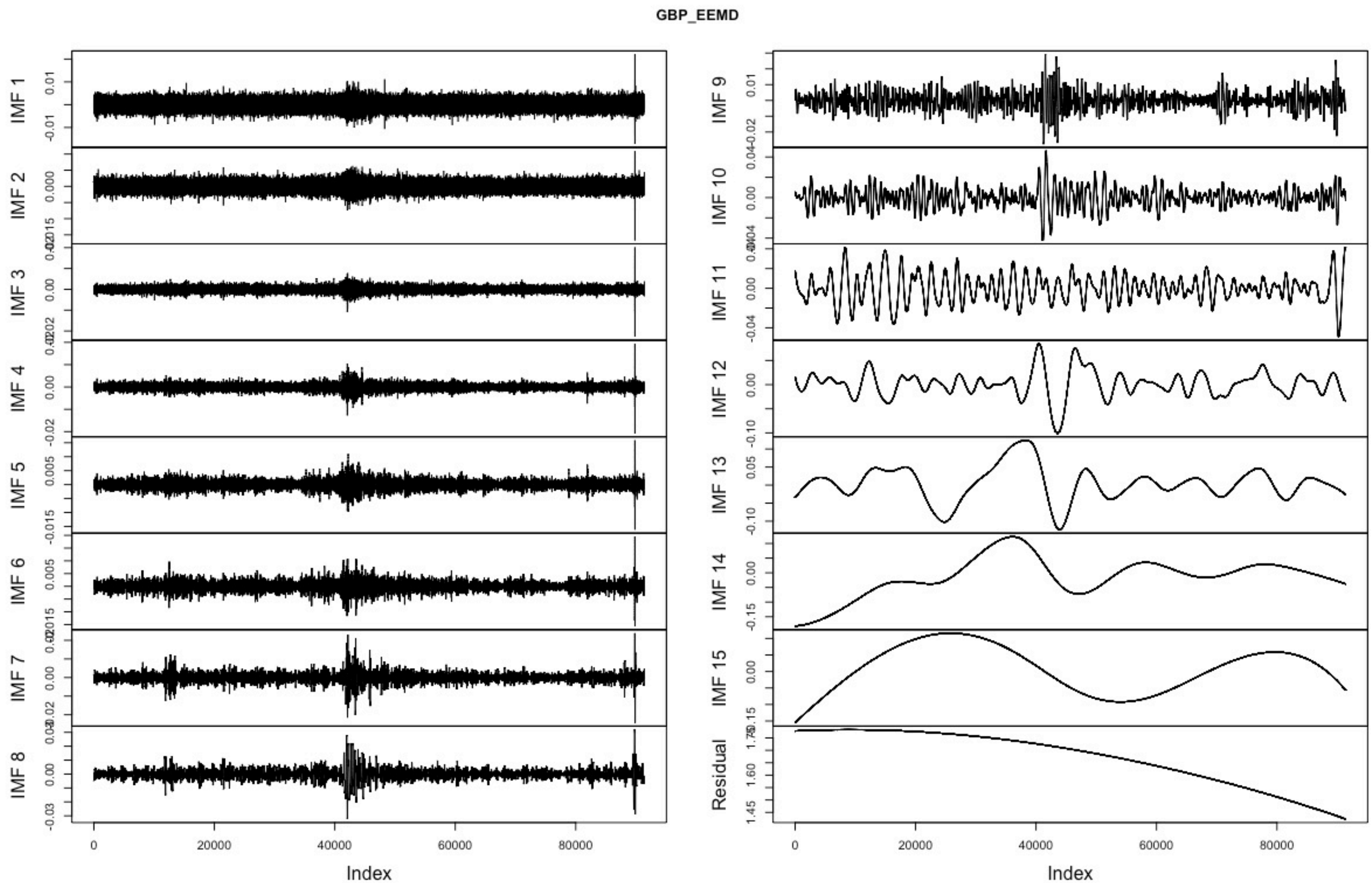

Figure 8. EEMD on hourly GBP/USD closing prices

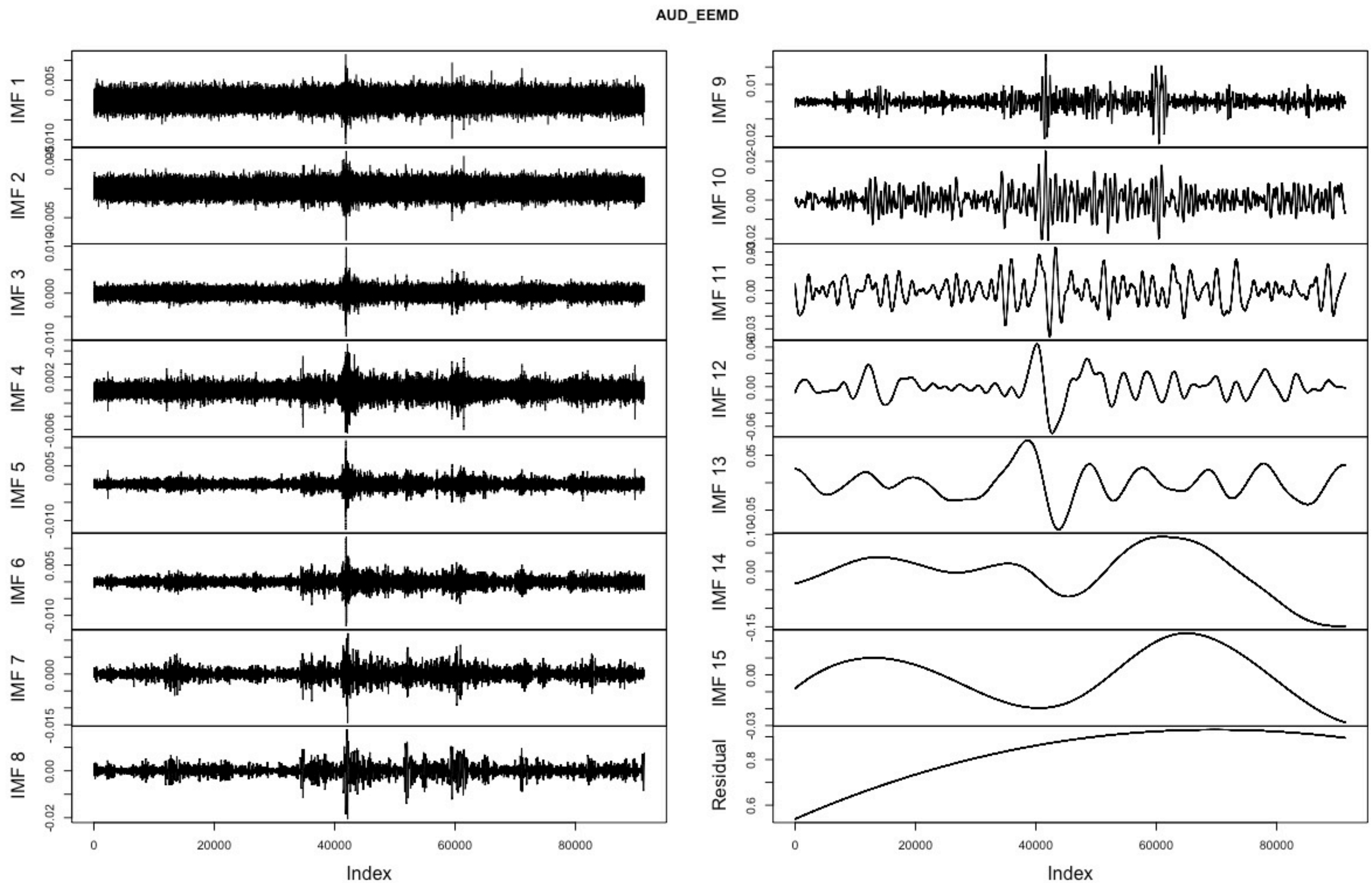

Figure 9. EEMD on hourly AUD/USD closing prices

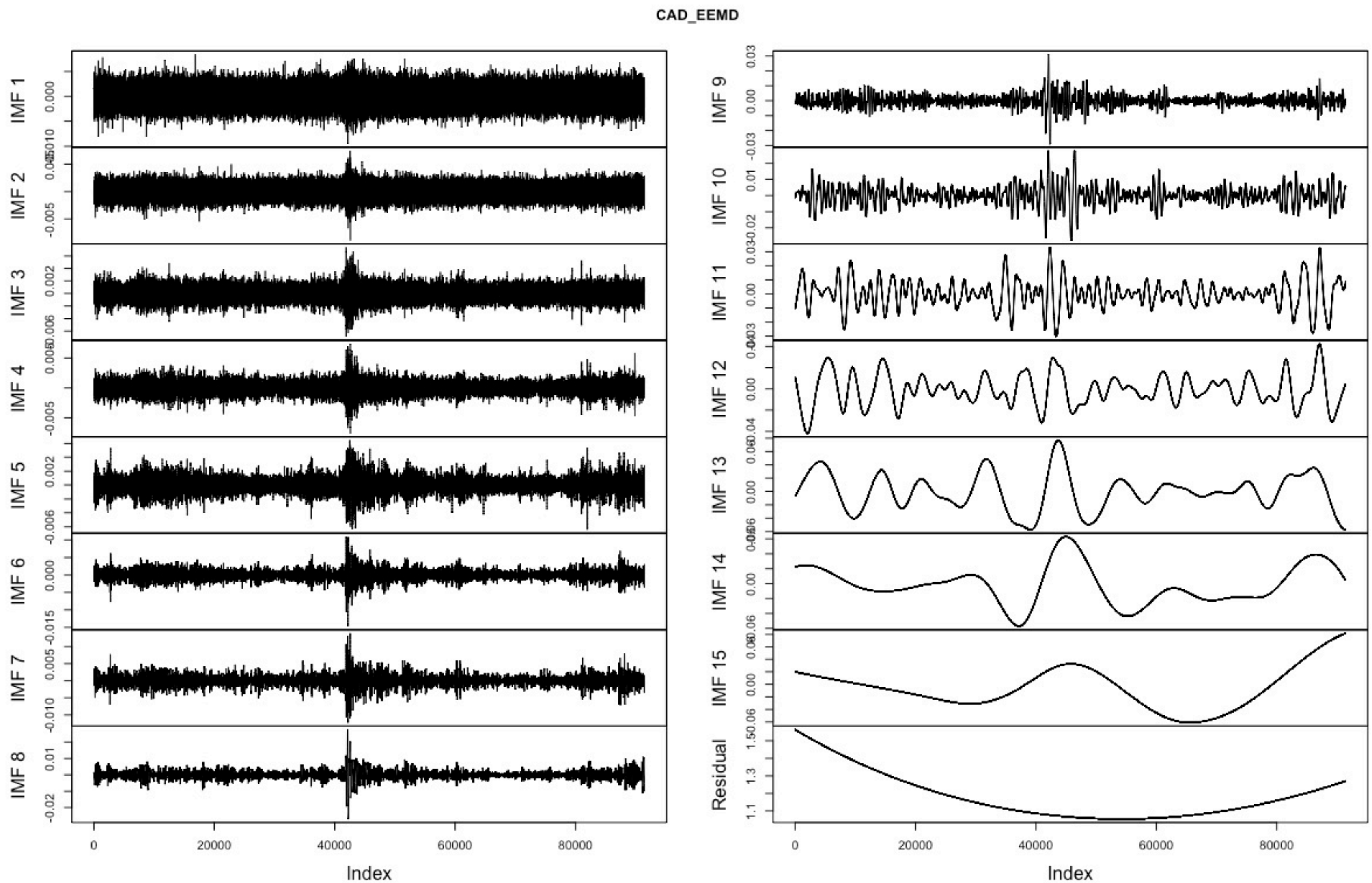

Figure 10. EEMD on hourly USD/CAD closing prices

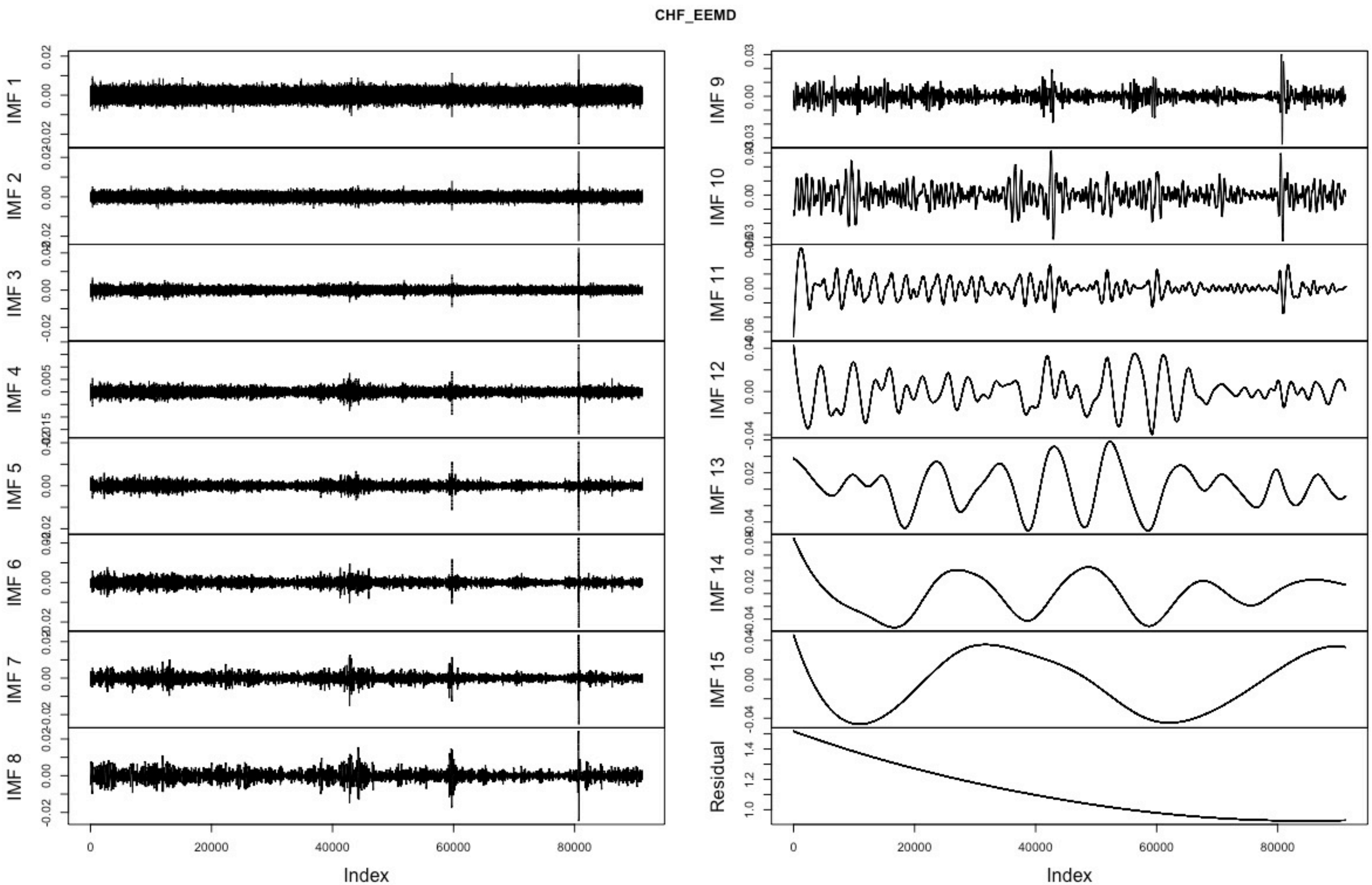

Figure 11. EEMD on hourly USD/CHF closing price

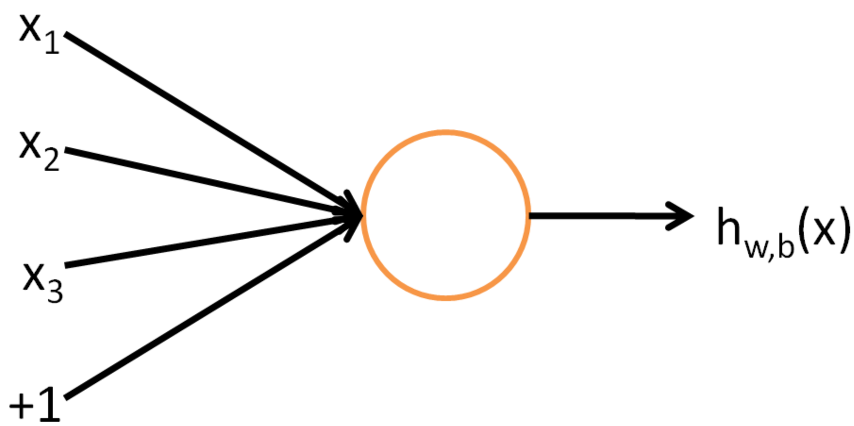

Figure 12. Single neuron feedforward network

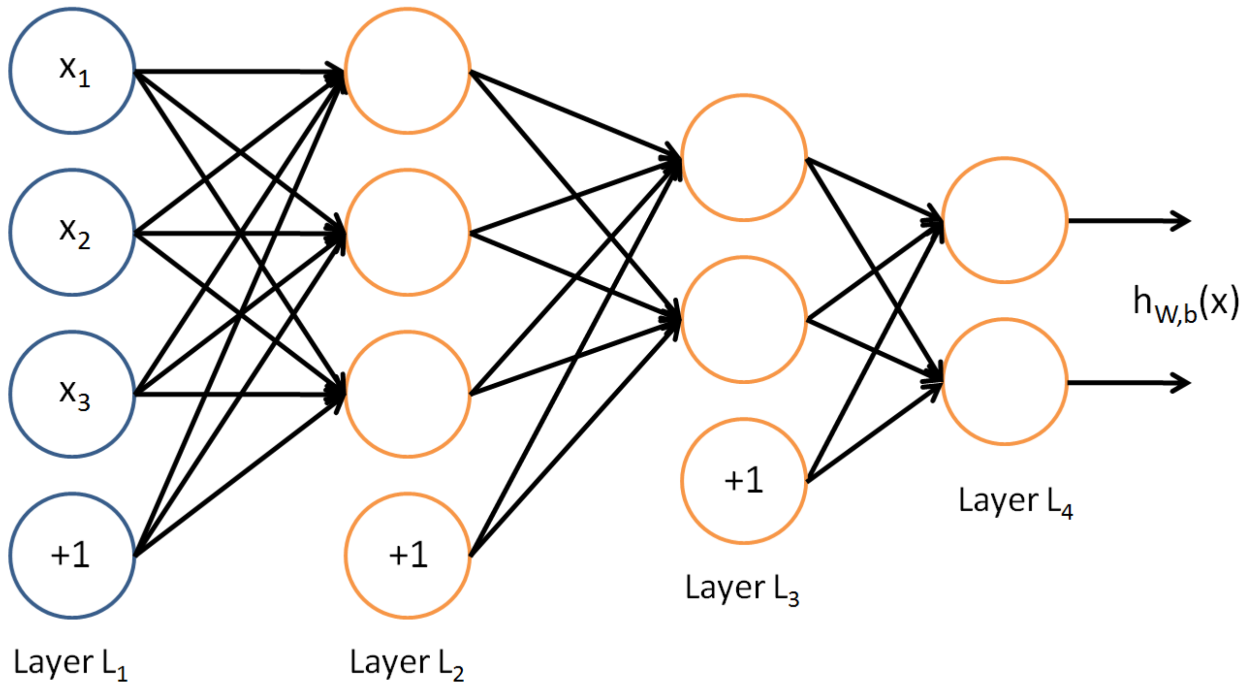

Figure 13. Multiple-layer feedforward networks

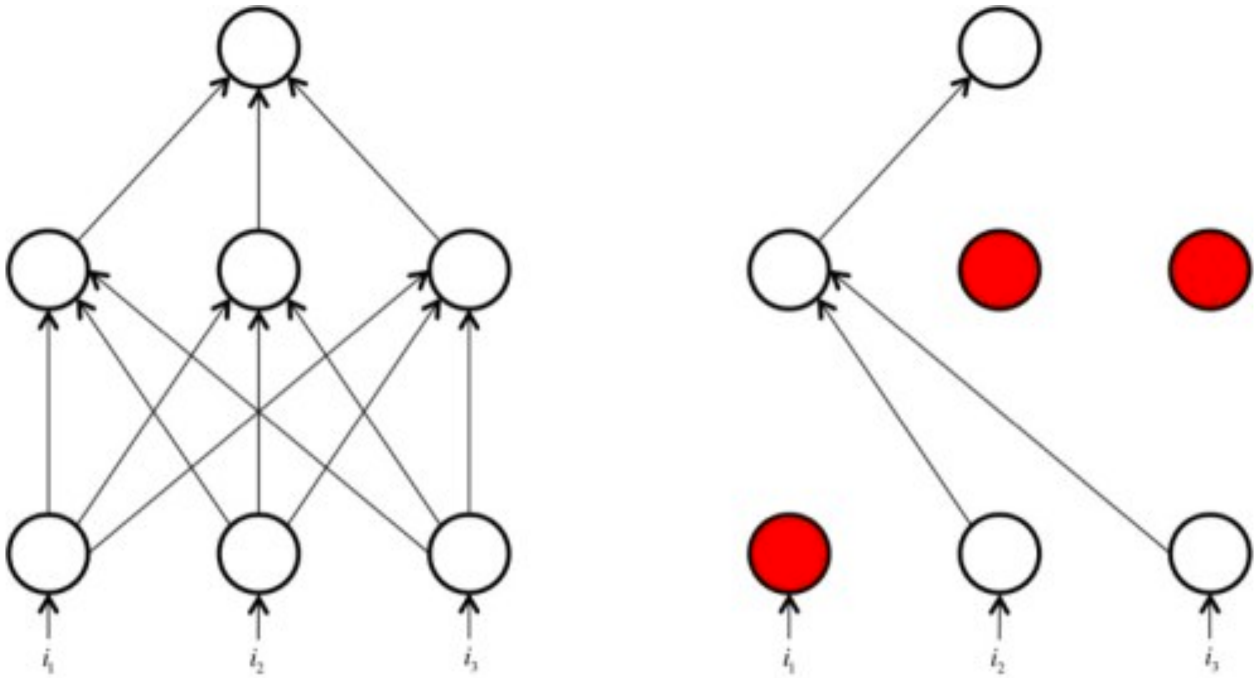

Figure 14. Dropout in neural networks