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Empirical mode decomposition and ANFIS network-based prediction technique for financial forecasting

A. Akbari, M. Faridi Masoule*, A. Bagheri, S. Nezamivand Cheghini[b]

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Abstract A financial market is non-linear and chaotic in nature. So, the accurate prediction of foreign exchange rate is very difficult and challengeable task. Hence, many proposed techniques and new approaches are used for forecasting various countries' exchange rates with different parameters. This paper proposes EMD-ANFIS for foreign currency exchange rate prediction. In this research, we would like to propose a model which could develop multivariate exchange rates information and put these features to better use. The performance of the proposed system has been tested with European EURO against US Dollar (EUR/USD), British POUND against US Dollar (GBP/USD), US Dollar against Swiss FRANK (USD/CHF), US Dollar against Japanese YEN (USD/JPY) and used to predict one day exchange rate in advance. Empirical mode decomposition (EMD) and QPSO (Quantum Particle Swarm Optimization) are techniques that used here which generates optimal weight for the proposed model. The proposed approach has been found with the best prediction rate against previous studies.

Keyword: ANFIS, QPSO, EWT, EMD.

1 Introduction

By considering the properties of nonlinear data and the impact of historical data, this study combines empirical mode decomposition (EMD) into wavelet ANFIS network with QPSO (Quantum Particle Swarm Optimization) to establish a hybrid ANFIS network prediction approach to improve the prediction accuracy of forecasting various countries' exchange rates.

2 Basic Methods

2.1 ANFIS

* **Corresponding Author. (✉)**
E-mail: m.faridi@ahrar.ac.ir (M. Faridi Masoule)

A. Akbari
Department of Computer and Information Technology, Ahrar Institute of Technology and Higher Education, Rasht, Iran

M. Faridi Masoule
Department of Computer and Information Technology, Ahrar Institute of Technology and Higher Education, Rasht, Iran

A. Bagheri
Department of Dynamic, Control, and Vibration, Faculty of Mechanical Engineering, University of Guilan, Rasht, Iran

S. Nezamivand Cheghini
Department of Dynamic, Control, and Vibration, Faculty of Mechanical Engineering, University of Guilan, Rasht, Iran

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The fuzzy logic theorem, introduced by Zadeh [1] for the description of complicated systems, has gained widespread popularity and applications in solving problems related to predictions specifically for water level in reservoirs [2]. Yet, the critical issue lies in the lack of a systematic procedure for the design of a fuzzy controller. In addition, a neural network can learn from the environment (input–output pairs), organize its structure by itself, and adapt to the environment interactively. Thus, the adaptive neuro-fuzzy inference system (ANFIS) methodology is proposed to be used for the self-organization of the network structure and the parameters of the fuzzy system are adjusted for financial forecasting.

2.2 QPSO

QPSO (Quantum-behaved Particle Swarm Optimization), proposed by Sun, Feng, and Xu [3] and Sun, Xu, & Feng [4, 5], has particles with quantum behavior, revolving around the potential field. QPSO does not assign each particle with position and velocity, but with Q a wave function w(x, t), instead. There is a difference between the behavior of particles in QPSO and PSO. The probability density function w(x, t) determines the probability of the appearance of the particle i in position x. Each particle moves following Eqs. (1) and (2) Q3

$$Pid = \varphi.\ Pid + (1-\varphi).\ Pgd \qquad \varphi = rand\ () \tag{1}$$

$$Xid = Pid \pm \alpha.\ |\ mbestd - xid\ |\ \ln(1/u) \qquad u \sim U(0.1) \tag{2}$$

where, mbest is the mean best position of the particles.

$$Mbest = \frac{1}{M}\sum Pi = \left(\frac{1}{M}\sum Pi1, \frac{1}{M}\sum Pi2, \dots\dots\dots\dots\dots \frac{1}{M}\sum Pin\right) \tag{3}$$

Pid is a random point between Pid and Pgd and a local attractor for the i-th particle on the d-th dimension. u and u are random numbers in [0 1] and a is one of the QPSO parameters, called the contraction–expansion coefficient.

2.3 EMD

As a method for analyzing a signal without leaving the time domain, EMD can be compared with other methods like Fourier Transforms and wavelet decomposition. This is a useful process for the analysis of natural signals. Such signals are mostly non-linear and non-stationary. EMD eliminates functions that shape a complete and partly orthogonal basis for the original signal. The basis of completeness depends on the EMD method and how it is decomposed. Even though the functions, commonly referred to as Intrinsic Mode Functions (IMFs), are not necessarily orthogonal, they can sufficiently be used for the description of the signal.

The varying frequency in time can be preserved because the functions into which a signal is decomposed are of the same length as the original signal and are in the time-domain. It is important to obtain IMFs from real world signals because there are often multiple causes for natural processes, and these causes are likely to occur at specific time intervals. This type of data cannot be seen in Fourier domain or in wavelet coefficients but is completely visible in an EMD analysis.

The EMD method may effectively be applied in sea-surface height (SSH) readings, seismic readings, results of neuroscience experiments, gastroelectrograms, and electrocardiograms. [6]

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2.4 EWT

By employing an adaptive wavelet subdivision scheme, the empirical wavelet transform (EWT) yields a multiresolution analysis (MRA) of a signal. By means of this technique, the signal's spectrum is segmented and perfect reconstruction of the input signal is provided. Gilles [7] developed the EWT and for the segmentation of the spectrum, Gilles and Heal [8] proposed and employed a histogram-based approach.

In an MRA, a signal is decomposed into components on different scales or frequency bands. In this way, the original signal can be recovered by collecting the components at each point in time (see Practical Introduction to Multiresolution Analysis). There are several MRA techniques. The maximal overlap discrete wavelet transform (MODWT) and its associated MRA formulation employ a frame that can function without requiring the signal. As a data-adaptive technique, the EMD algorithm decomposes a nonlinear or nonstationary process into its intrinsic modes of oscillation. To obtain natural AM-FM modes, also known as intrinsic mode functions, contained in the data, the EMD repeats on an input signal [9].

3 Proposed Method

Applying EMD to Forex data to remove noise begins the data preprocessing process. In the data preprocessing section, we first use the EMD method, whose threshold is a number between 0 and 1. Results for values 0.1 and 0.2 give the best input for ANFIS. So after checking, the threshold is set to 0.1(threshold value=0.1).

In this section, the EWT method is also examined. In this method, the value of FS must be specified. In fact, FS is the signal sampling rate per second (the sampling rate of the signal) that is considered for us every working day and is 1 over 86400.

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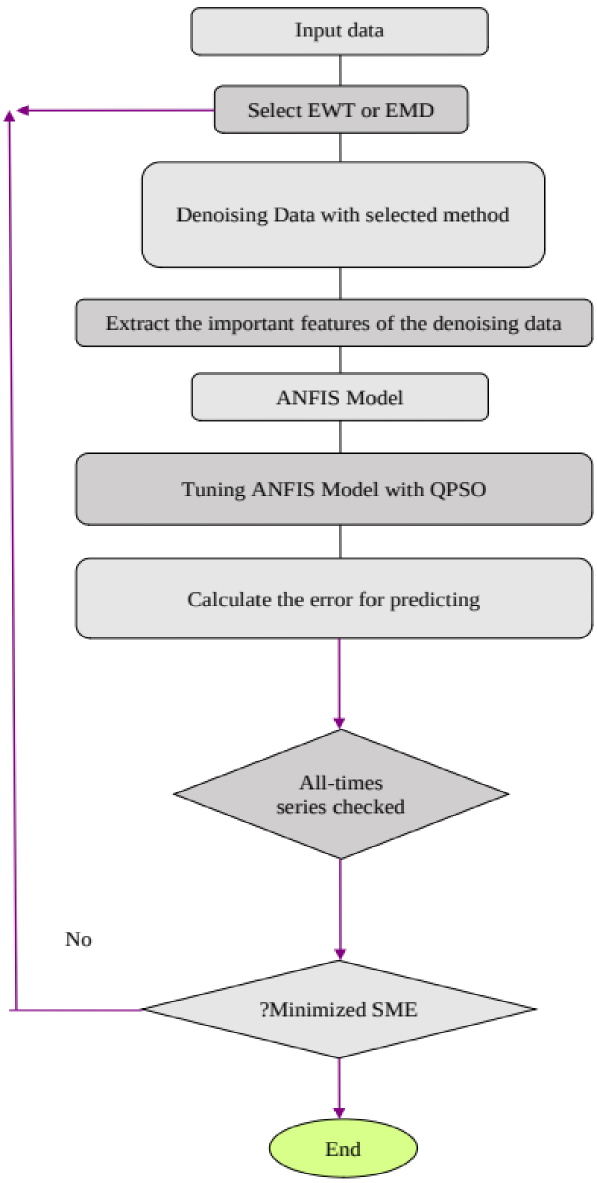

Fig. 1 Flowchart of the proposed forecasting model

As can be seen in the flowchart of the proposed model in Figure 1, both EMD and EWT methods are applied simultaneously to eliminate noise, and after comparing the output of both methods, EMD is selected as the optimal method.

3.1 EWT and ANFIS-QPSO

In this section, the EWT method is first applied to all four sets of EUR/USD, GBP/USD, USD/CHF and USD/JPY that noise is removed (Fig 2 to Fig 5).

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We utilized four major currency pairs - EUR/USD, GBP/USD, USD/CHF, and USD/JPY for evaluating the proposed EMD-ANFIS model. For each currency pair, we first denoised the raw data using EWT and EMD techniques separately.

We have presented the training and test datasets generated after EWT denoising for each currency in Figures 6-13. Specifically, Figures 6 and 10 illustrate the USD/JPY training and test data after applying EWT noise removal. Figures 7 and 11 display the USD/CHF training and test datasets after EWT filtering. The EWT denoised training and test datasets for GBP/USD are shown in Figures 8 and 12, while those for EUR/USD are depicted in Figures 9 and 13.

Additionally, we have also applied EMD denoising on the raw currency data and provided the resulting training and test datasets in Figures 18-25. In particular, Figures 18 and 22 present the training and test data for USD/JPY following EMD noise removal. The EMD filtered training and test datasets for USD/CHF are illustrated in Figures 19 and 23. Figures 20 and 24 display the EMD denoised GBP/USD training and test data. Finally, Figures 21 and 25 show the training and test datasets for EUR/USD after applying EMD noise filtering.

We utilized the EWT and EMD filtered training datasets to develop the ANFIS models with optimized parameters by QPSO. The EWT-ANFIS and EMD-ANFIS models were then evaluated on the corresponding test datasets to compare their out-of-sample forecasting performance. Our results showed that EMD-ANFIS achieved superior prediction accuracy over EWT-ANFIS and standalone ANFIS models.

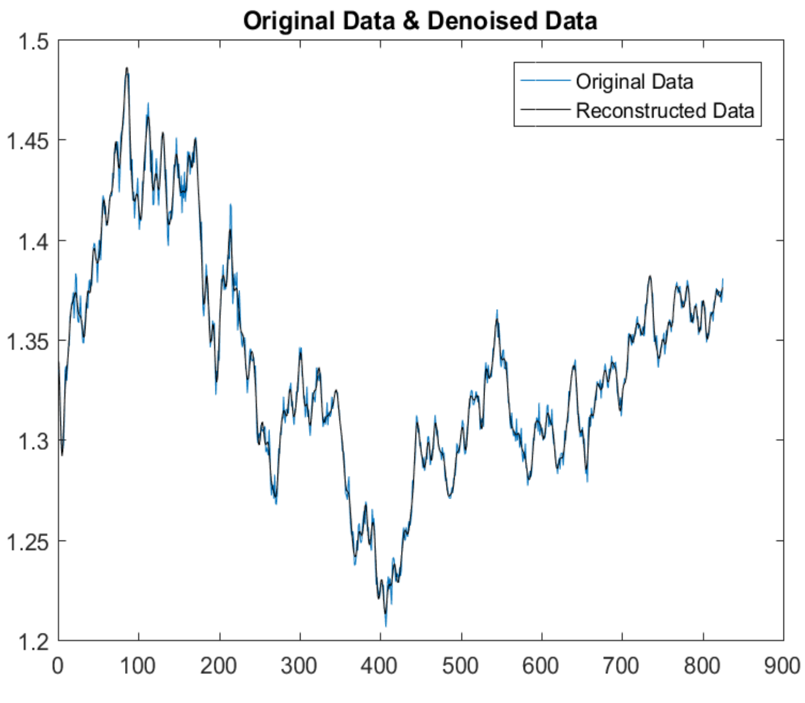

Fig. 2 Denoising EUR/USD with EWT

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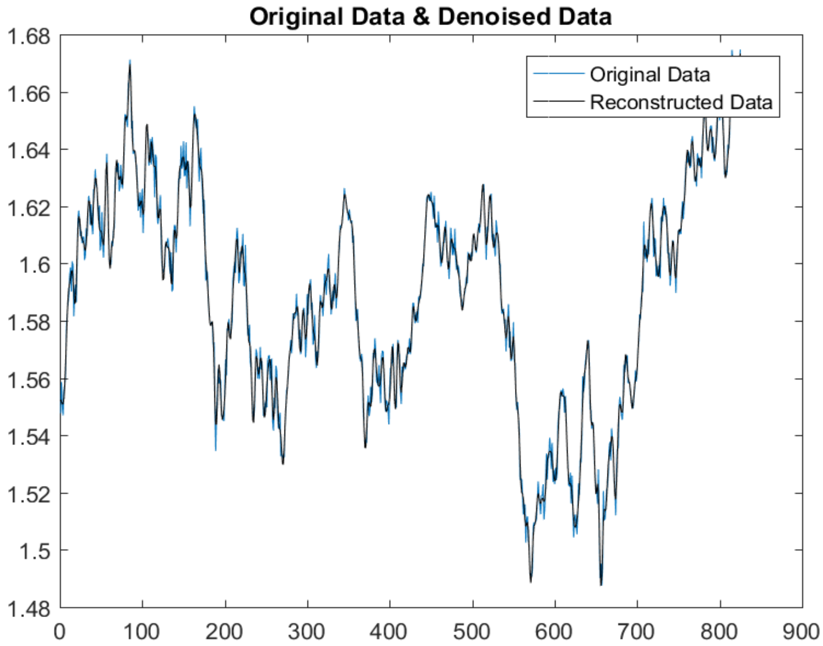

Fig. 3 Denoising GBP/USD with EWT

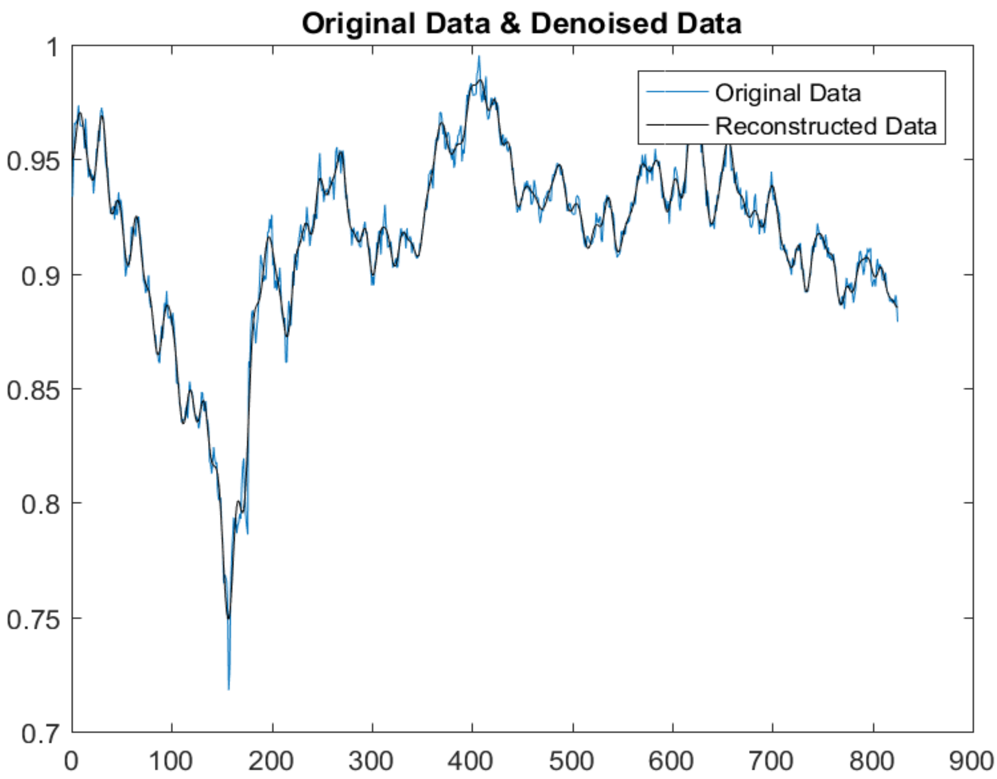

Fig. 4 Denoising USD/CHF with EWT

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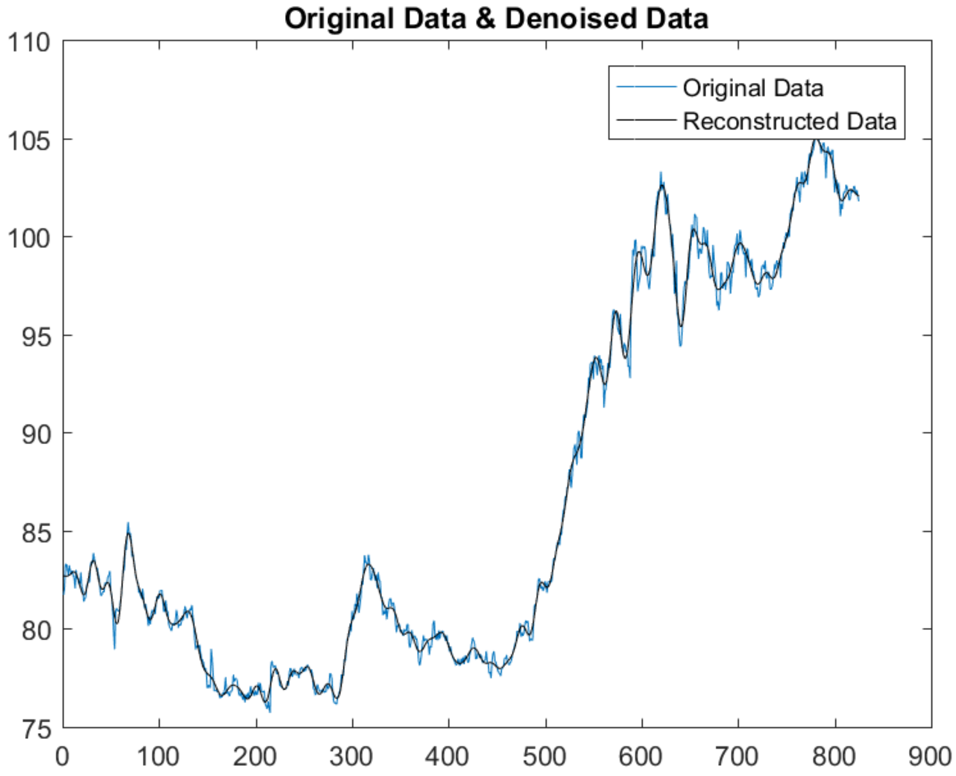

Fig. 5 Denoising USD/JPY with EWT

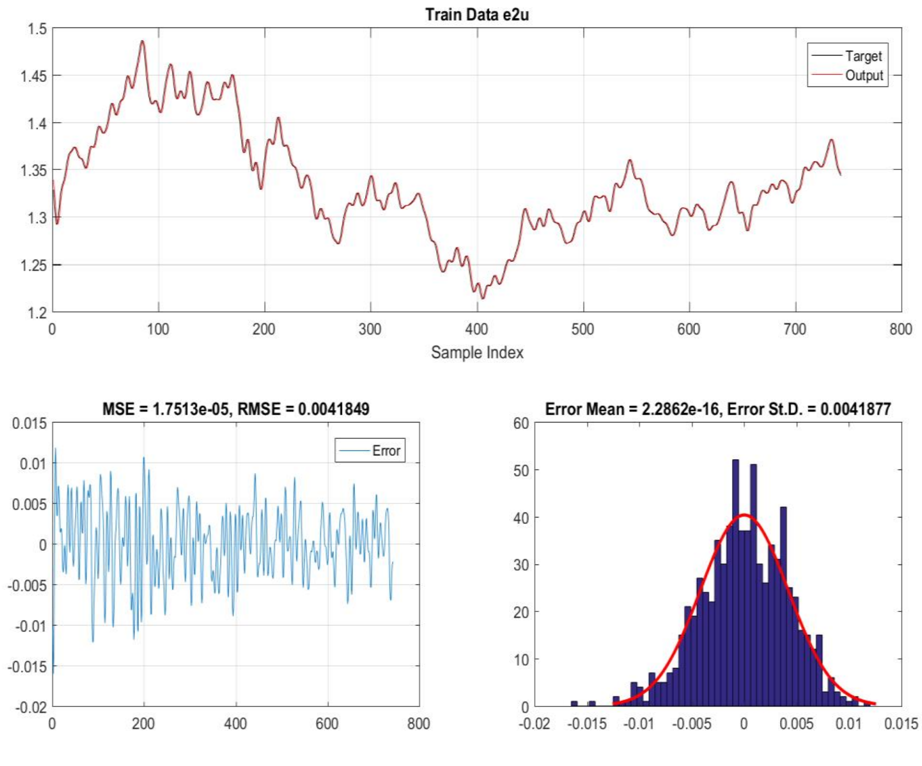

Fig. 6 Training Dataset USD/JPY with EWT

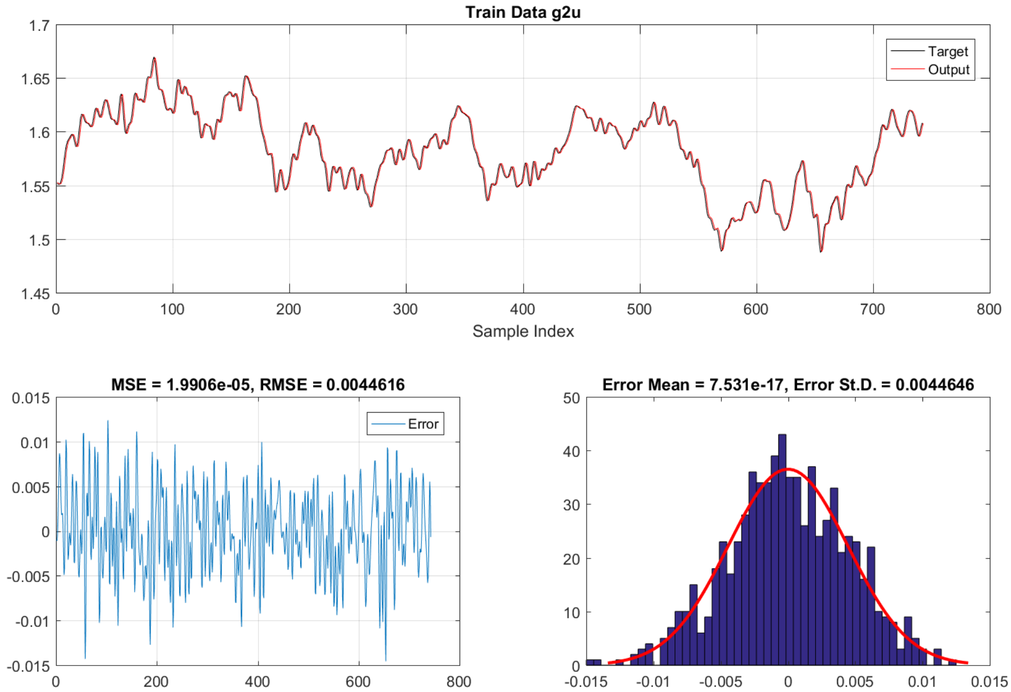

Fig. 7 Training Dataset USD/CHF with EWT

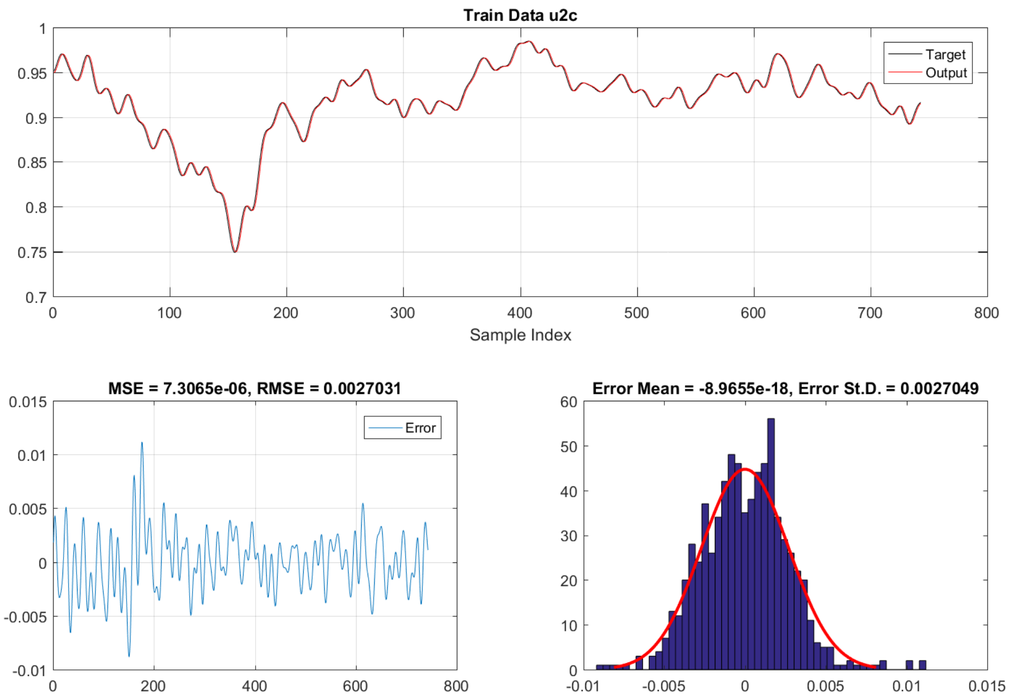

Fig. 8 Training Dataset GBP/USD with EWT

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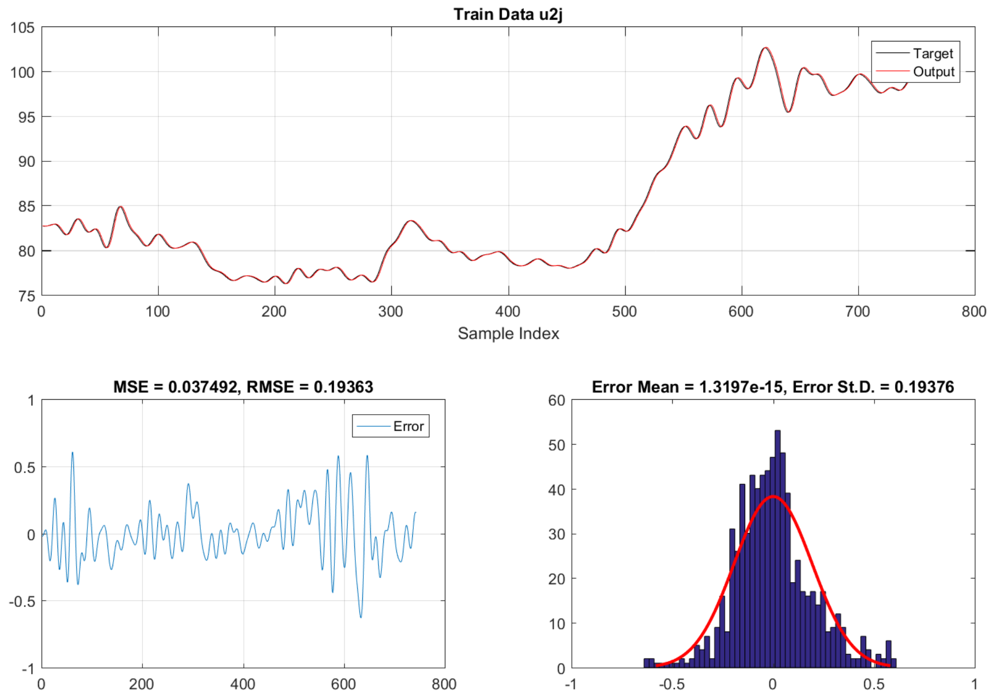

Fig. 9 Training Dataset EUR/USD with EWT

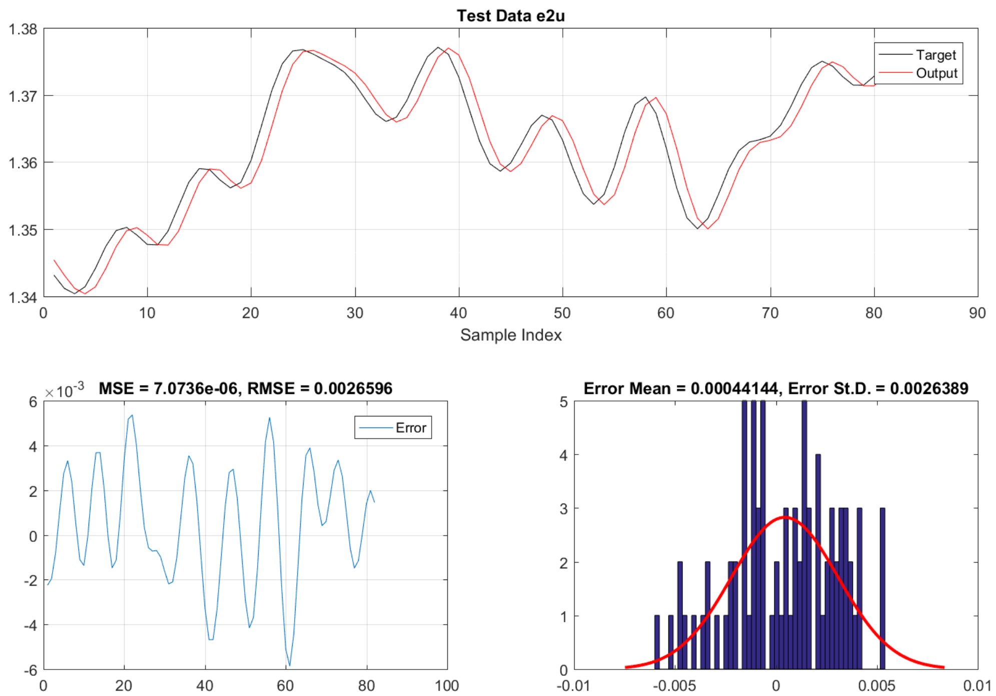

Fig. 10 Test Dataset USD/JPY with EWT

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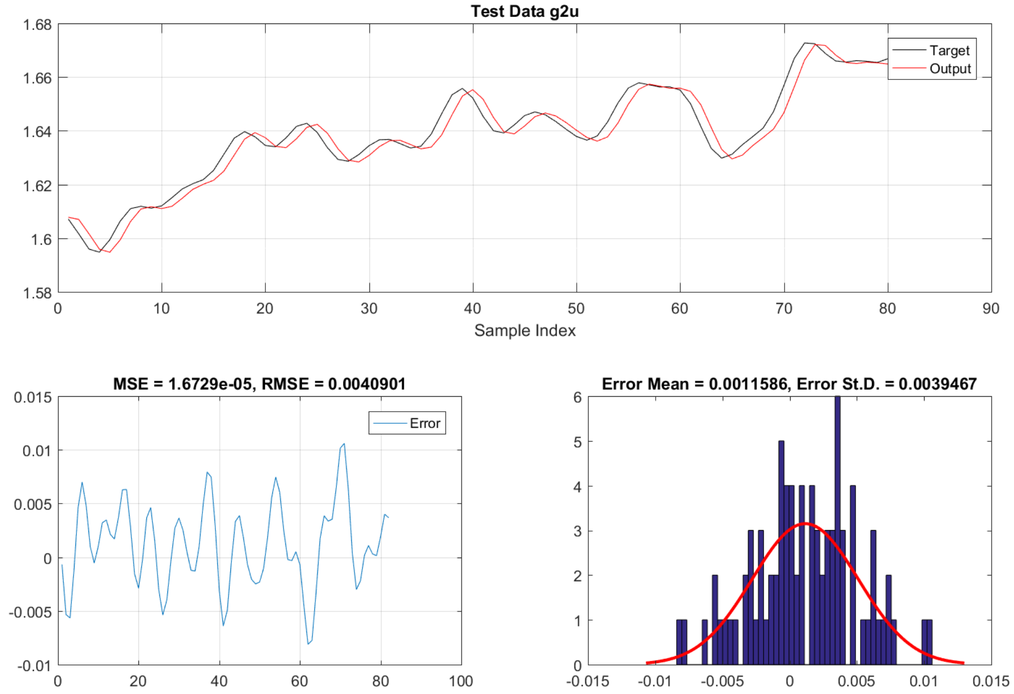

Fig. 11 Test Dataset USD/CHF with EWT

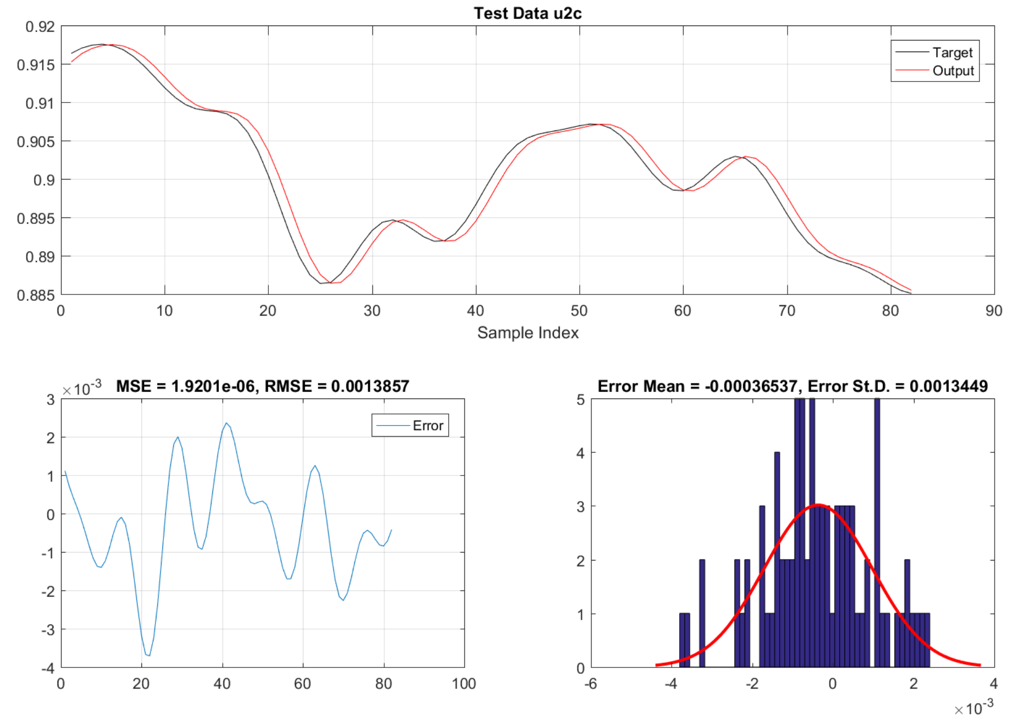

Fig. 12 Test Dataset GBP/USD with EWT

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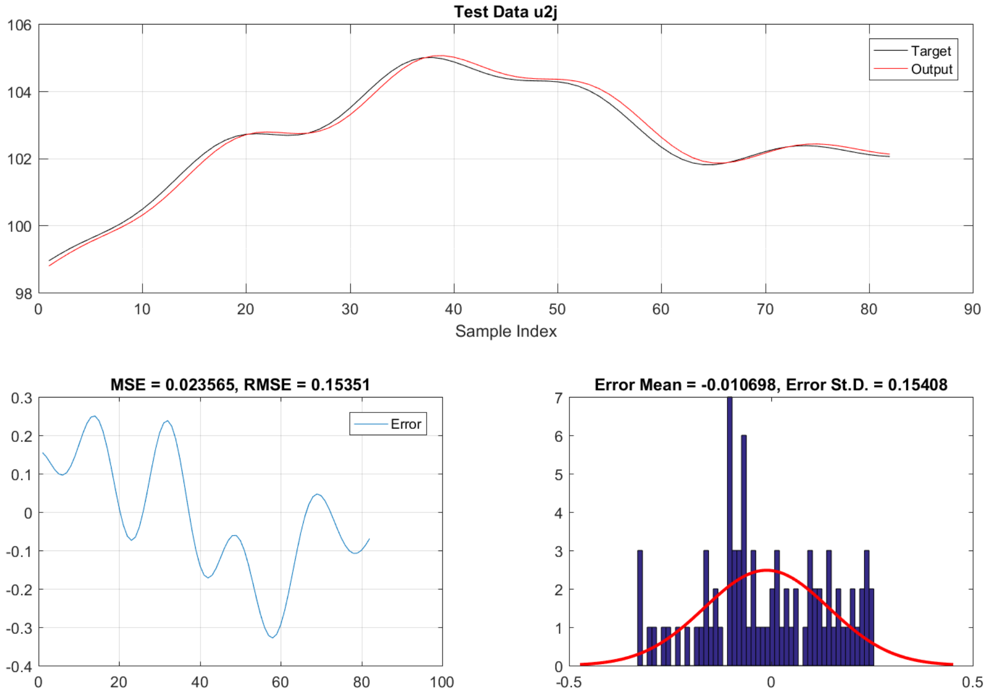

Fig. 13 Test Dataset EUR/USD with EWT

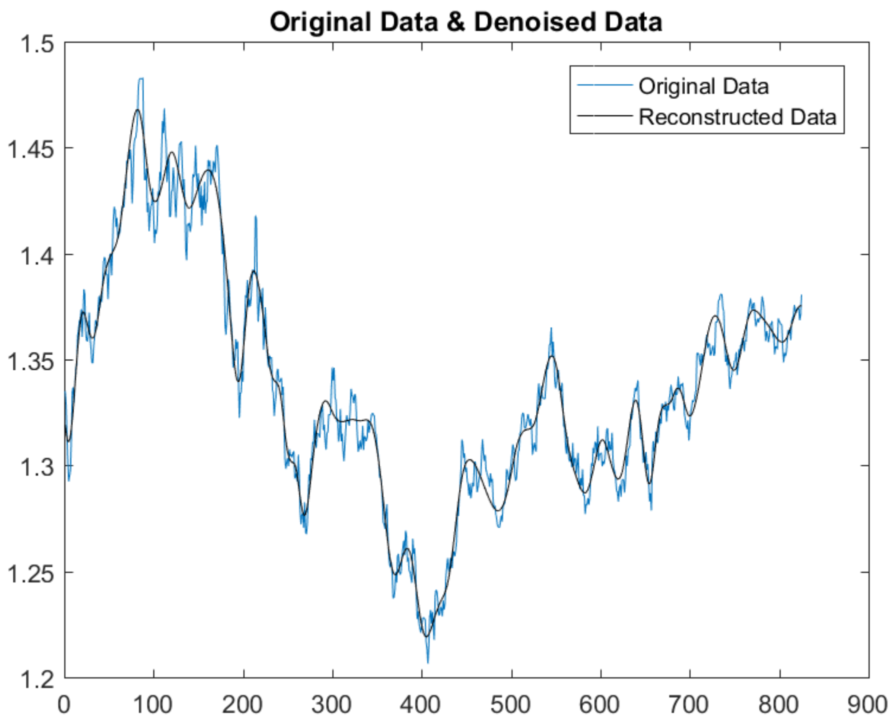

Fig. 14 Denoising EUR/USD with EMD

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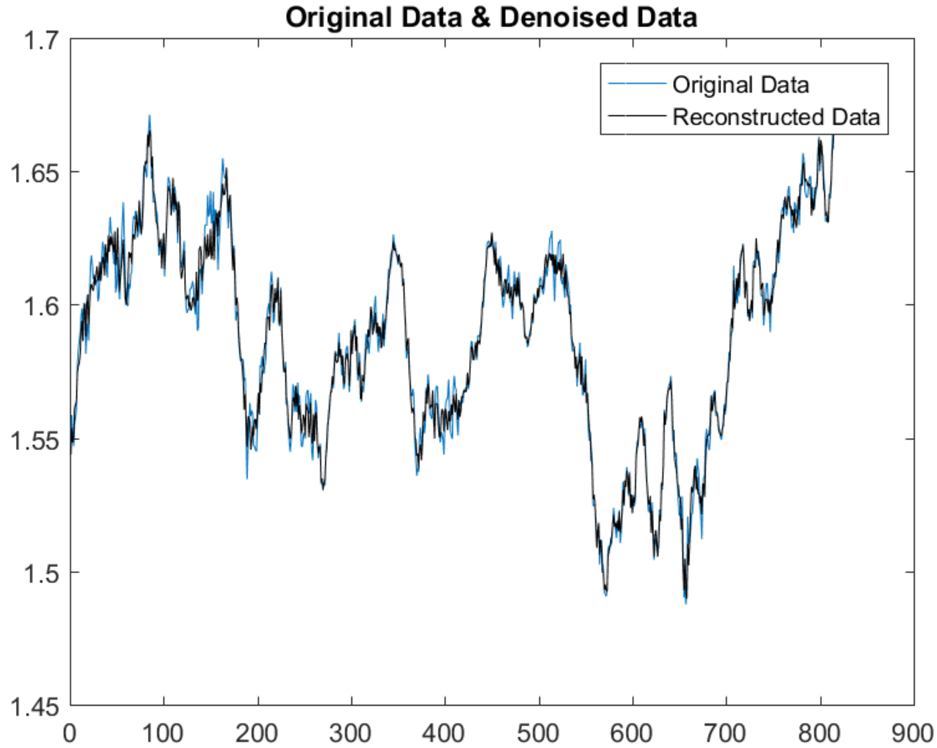

Fig. 15 Denoising GBP/USD with EMD

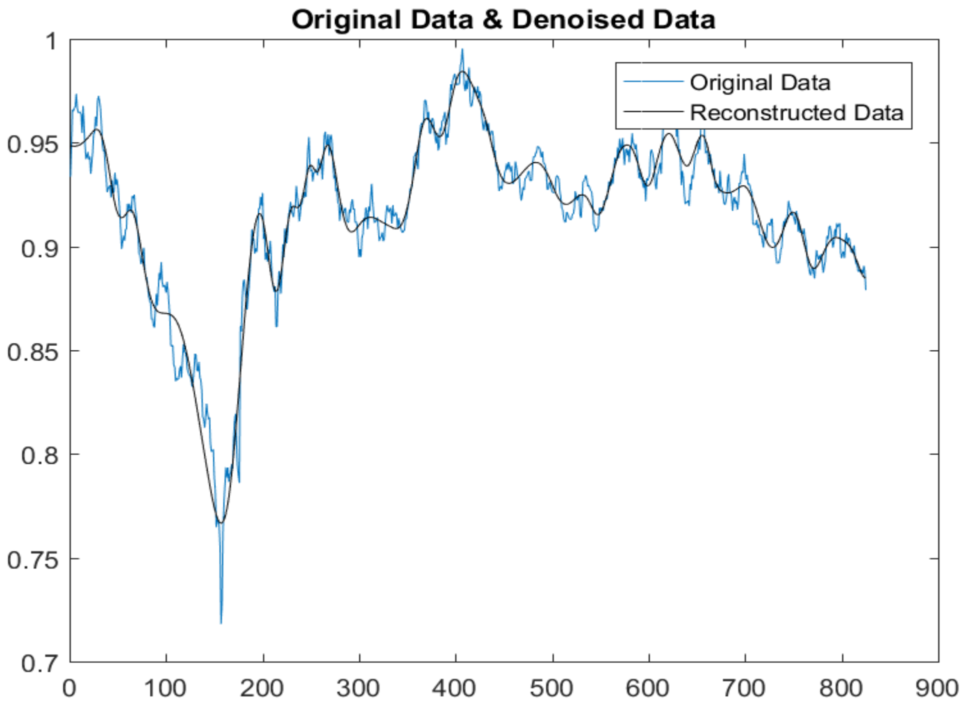

Fig. 16 Denoising USD/CHF with EMD

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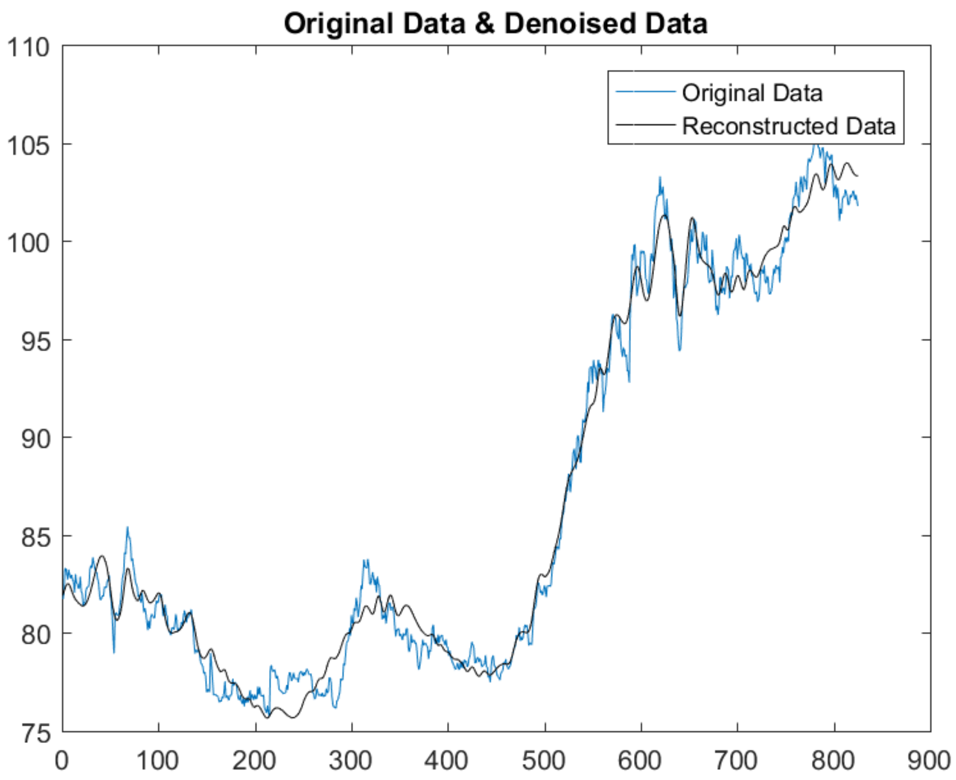

Fig. 17 Denoising USD/JPY with EMD

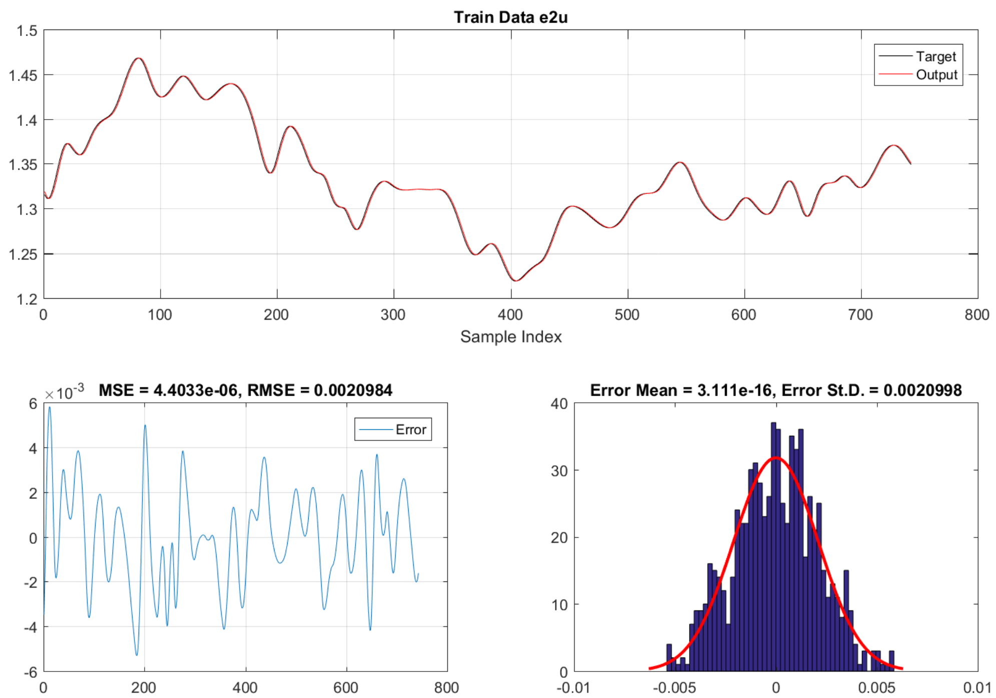

Fig. 18 Training Dataset USD/JPY with EMD

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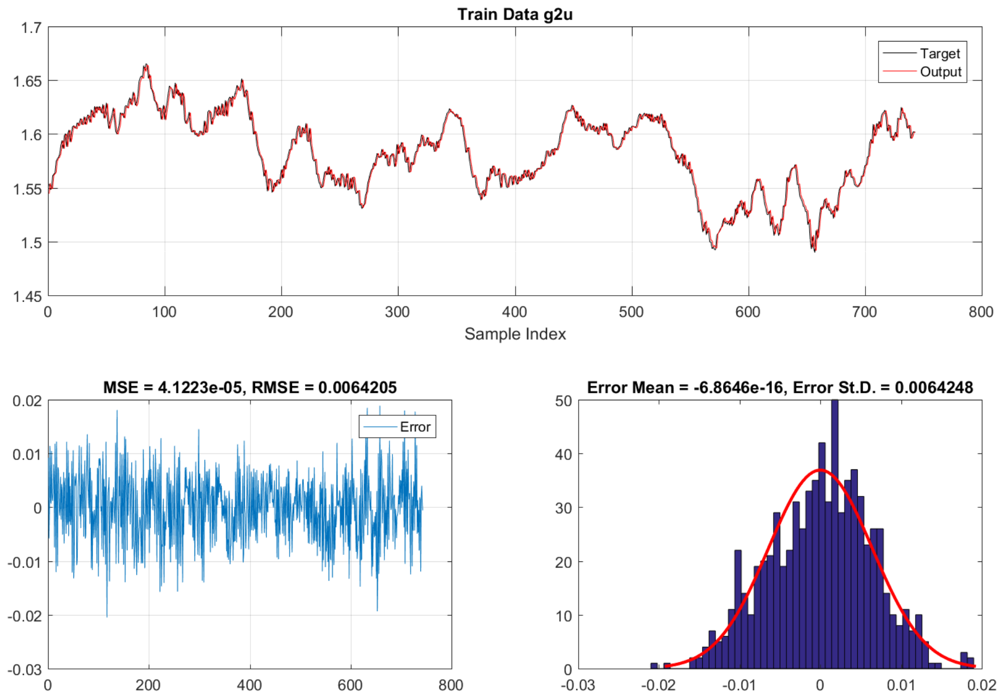

Fig. 19 Training Dataset USD/CHF with EMD

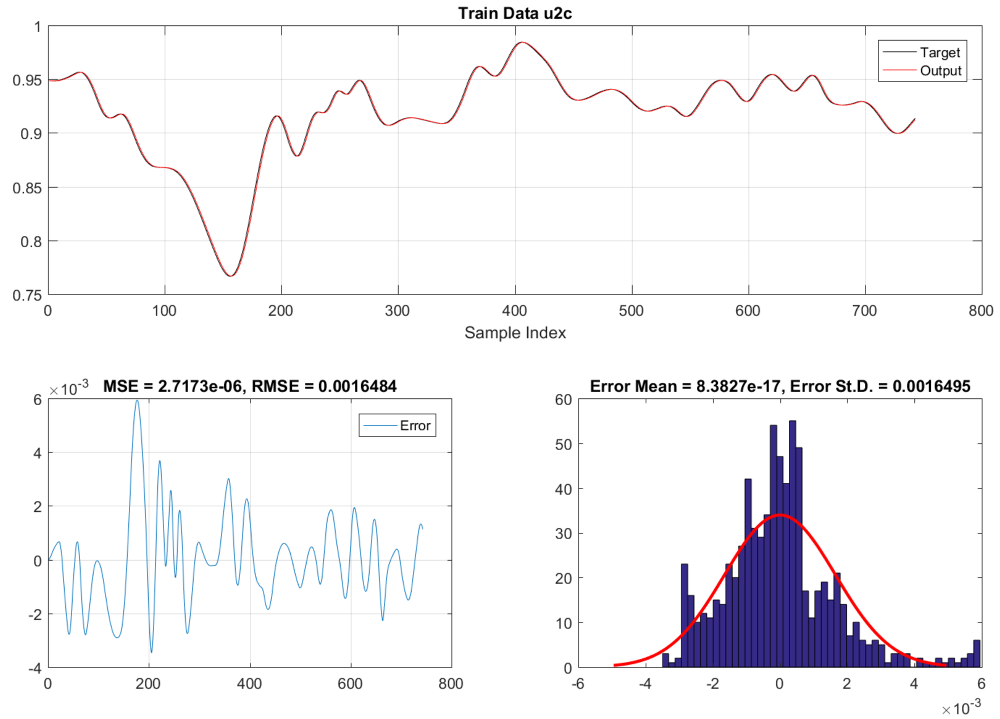

Fig. 20 Training Dataset GBP/USD with EMD

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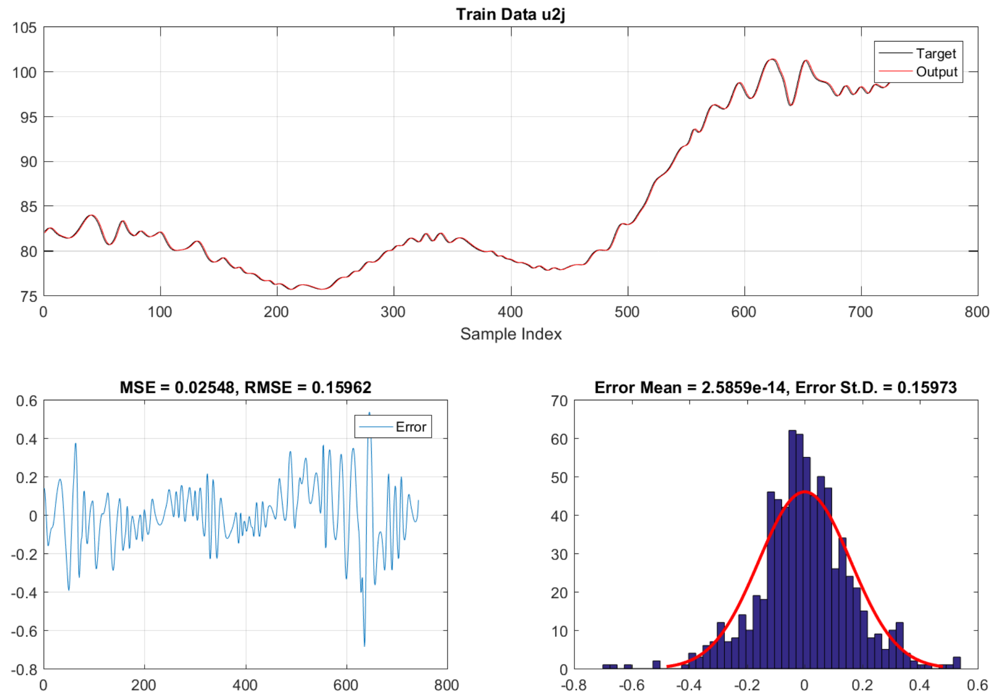

Fig. 21 Training Dataset EUR/USD with EMD

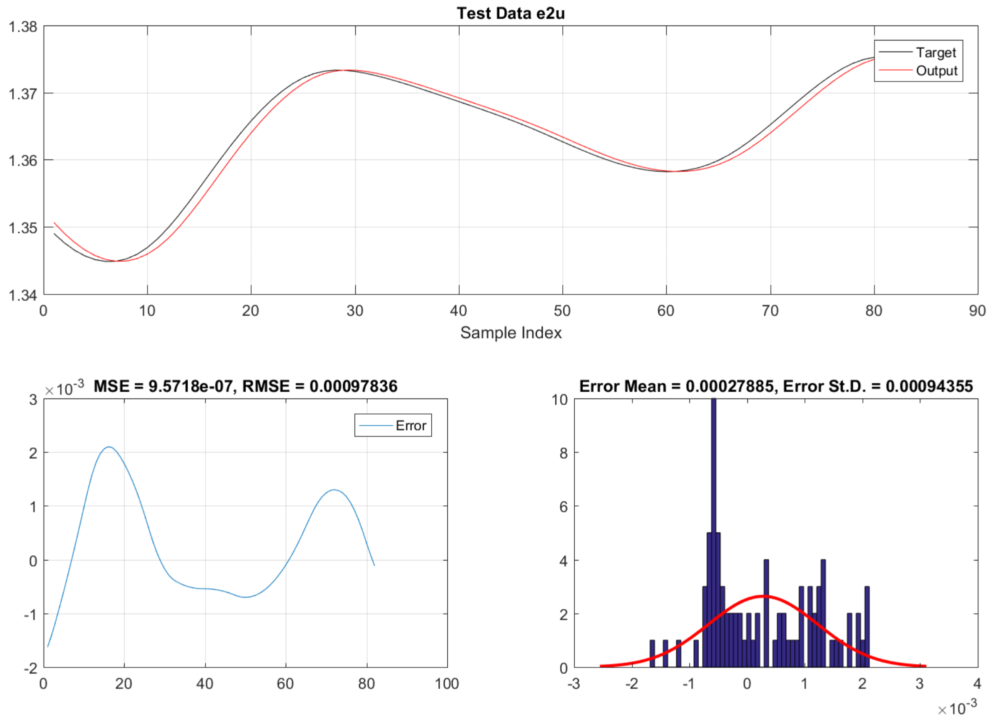

Fig. 22 Test Dataset USD/JPY with EMD

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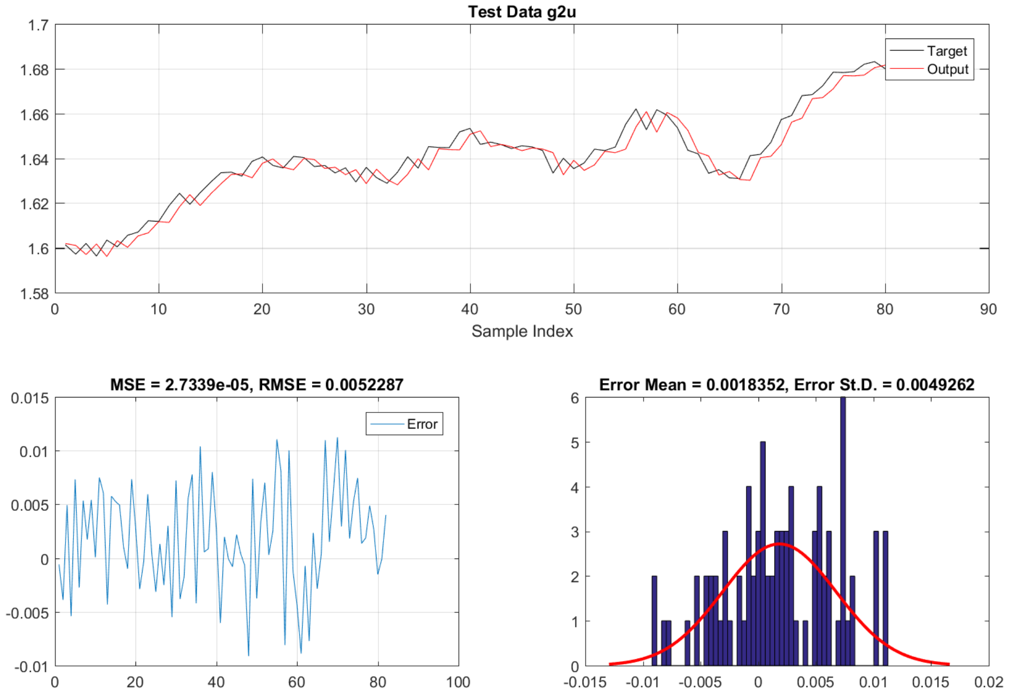

Fig. 23 Test Dataset USD/CHF with EMD

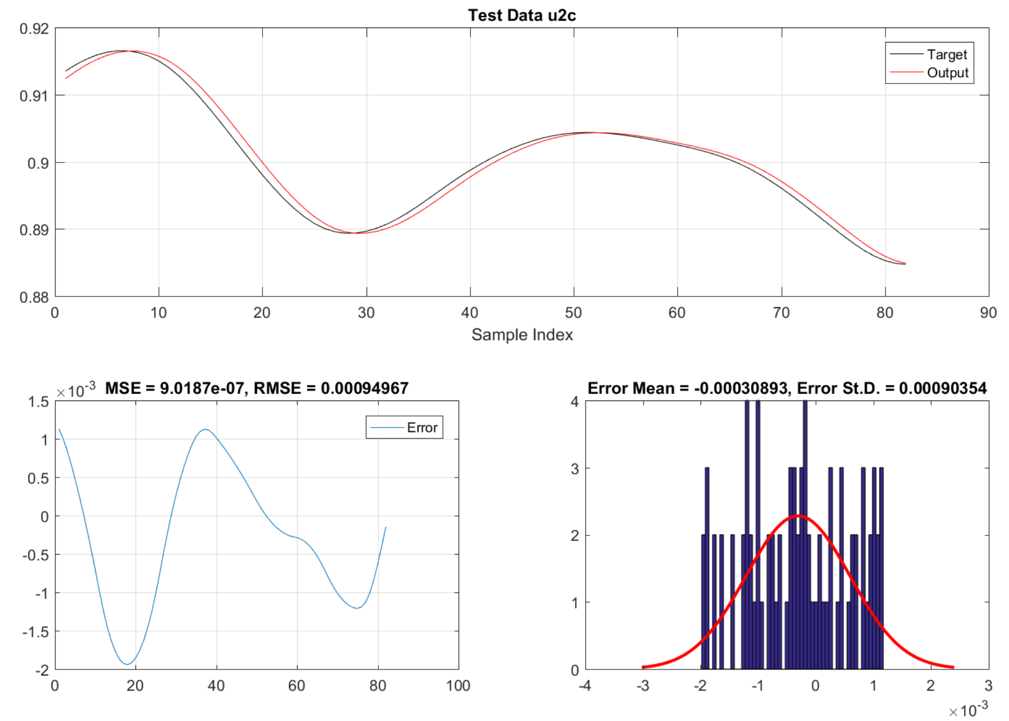

Fig. 24 Test Dataset GBP/USD with EMD

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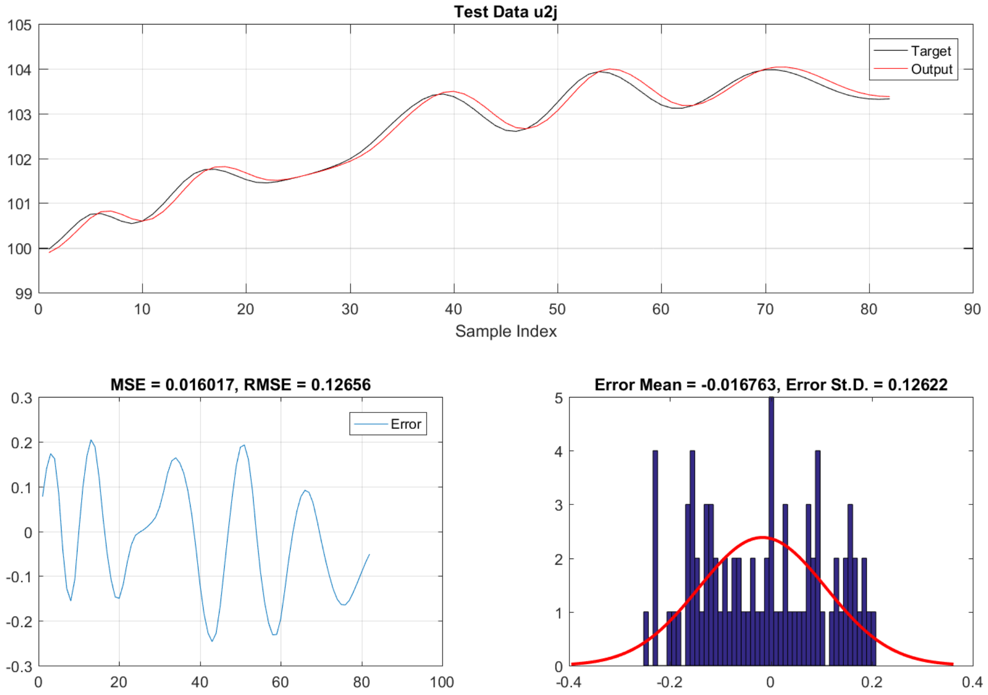

Fig. 25 Test Dataset EUR/USD with EMD

Evaluating the forecast model (RMSE on Test Data)

	ANFIS(Base)	ANFIS-WT	ANFIS-EMD	ANFIS-EWT
EUR/USD	0.003472	0.0032106	0.00097836	0.0026596
GBP/USD	0.004781	0.004420	0.0052287	0.0040901
USD/CHF	0.002898	0.0030785	0.00094967	0.0013857
USD/JPY	0.454605	0.360190	0.126560	0.153510
AVE	0.116439	0.092724775	**0.033429**	0.04041135

Evaluating the forecast model (RMSE on Training Data)

	ANFIS(Base)	ANFIS-WT	ANFIS-EMD	ANFIS-EWT
EUR/USD	Not Reported	0.0059202	0.0020984	0.0041849
GBP/USD	Not Reported	0.0053626	0.0064205	0.0044616
USD/CHF	Not Reported	0.0051015	0.0016484	0.0027031
USD/JPY	Not Reported	0.407480	0.159620	0.193630
AVE	Not Reported	0.105966075	**0.042446825**	0.0512449

4 Conclusion

This study proposed a hybrid EMD-ANFIS model with QPSO for optimizing parameters to improve the accuracy of financial forecasting. The model was evaluated on four major currency pairs - EUR/USD, GBP/USD, USD/CHF, and USD/JPY. The raw currency data was

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first denoised using EMD and EWT techniques separately. The denoised datasets were divided into training and test sets.

The EMD-filtered training data was used to develop the ANFIS prediction model with its parameters optimized by QPSO. The performance was tested on the out-of-sample EMD-filtered test data. For benchmarking, standalone ANFIS and EWT-ANFIS models were also trained and tested. Comparative results showed that the proposed EMD-ANFIS framework achieved the lowest RMSE on the test data across all four currency pairs.

The empirical analysis demonstrated the capability of the EMD method to effectively de-noise financial time series data. The integration of EMD with ANFIS and QPSO further improved modeling accuracy and out-of-sample forecasting performance. The proposed hybrid intelligent methodology provides an accurate and robust approach for financial time series forecasting. Future work may investigate the application of this model for other types of nonlinear and non-stationary financial data.

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