Economic Modelling 81 (2019) 49–58

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

A new multiscale decomposition ensemble approach for forecasting exchange rates

Shaolong Sun [a,b,c], Shouyang Wang [a,b,c], Yunjie Wei [a,c,*]

[a] Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China
[b] School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China
[c] Center for Forecasting Science, Chinese Academy of Sciences, Beijing 100190, China

ARTICLE INFO

Keywords:
Exchange rates forecasting
Variational mode decomposition
Support vector regression
Support vector neural network
Ensemble learning

ABSTRACT

Due to the high complexity and strong nonlinearity nature of foreign exchange rates, how to forecast foreign exchange rate accurately is regarded as a challenging research topic. Therefore, developing highly accurate forecasting method is of great significance to investors and policy makers. A new multiscale decomposition ensemble approach to forecast foreign exchange rates is proposed in this paper. In the approach, the variational mode decomposition (VMD) method is utilized to divide foreign exchange rates into a finite number of subcomponents; the support vector neural network (SVNN) technique is used to model and forecast each subcomponent respectively; another SVNN technique is utilized to integrate the forecasting results of each subcomponent to generate the final forecast results. To verify the superiority of the proposed approach, four major exchange rates were chosen for model comparison and evaluation. The experimental results indicate that our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach outperforms some other benchmarks in terms of forecasting accuracy and statistical tests. This demonstrates that our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is promising for forecasting foreign exchange rates.

1. Introduction

The foreign exchange rates are always characterized by high complexity and strong nonlinearity, since the exchange rates are affected by numerous unstable factors including economic conditions and political events. Developing highly accurate forecasting method is of great significance since it can provide requisite evidence for investors and policy makers to develop strategies and hedge risks. Currently, how to forecast foreign exchange rates accurately is still an open question with respect to the economic and social organization of modern society. Hence, some traditional econometric methods have been applied to forecasting exchange rates, such as linear regression models, autoregressive integrated moving average (ARIMA) model (Chortareas et al., 2011; Xiong et al., 2017), generalized autoregressive conditional heteroscedasticity (GARCH) model (Chortareas et al., 2011; West and Cho, 1995), vector auto-regression (VAR) model (Carriero et al., 2009; Joseph, 2001), co-integration model (McCrae et al., 2002; Moosa and Vaz, 2016) and error correction model (ECM) (Moosa and Vaz, 2016). The conventional econometric methods cannot capture the complexity and nonlinearity of the foreign exchange rates data, leading to weak forecasts. Therefore, it is very necessary for exchange rate forecasting to explore more effective forecasting models with sufficient learning ability. Hence, some advanced artificial intelligence (AI) techniques are proposed for forecasting exchange rates, such as support vector machine (SVM) (Huang et al., 2010), artificial neural networks (ANNs) (Özkan, 2013; Kuan and Liu, 1995; Zhang and Hu, 1998), and deep learning techniques (Shen et al., 2015).

The above non-linear artificial intelligence techniques have better forecasting performance than the conventional econometric models and statistical methods, but also have many issues, such as parameters optimization, local optimal problem and overfitting. Therefore, many hybrid ensemble approaches are used to solve the problem of time series prediction. (Chen and Leung, 2004; Garratt and Mise, 2014; Mostafa and El-Masry, 2016; Nag and Mitra, 2002; Bellalah et al., 2016; Sermpinis et al., 2012, 2013, 2015; Cheng et al., 2013; Wei, 2013; Yu et al., 2005). More importantly, Yu et al. (2008) proposed a decomposition-ensemble learning approach for the forecasting of crude oil spot price series. In this learning approach, the raw time series is decomposed into many

* Corresponding author. Postal Address: Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Zhongguancun East Road, # 55, Haidian District, Beijing, China.

E-mail addresses: sunshl@amss.ac.cn (S. Sun), sywang@amss.ac.cn (S. Wang), weiyunjie@amss.ac.cn (Y. Wei).

https://doi.org/10.1016/j.econmod.2018.12.013
Received 19 December 2017; Received in revised form 18 December 2018; Accepted 25 December 2018
Available online 26 December 2018

sub-models, which are easier to model and predict than the raw time series. Then the subcomponents are modeled separately. Finally, the ensemble learning tool is used to generate the final forecasting results by combining the sub-components forecasts. Presently, ensemble learning approaches have been widely applied in time series forecasting, such as energy consumption forecasting (Tang et al., 2012), crude oil spot prices forecasting (Yu et al., 2015), $PM_{2.5}$ concentration forecasting (Niu et al., 2016, 2017), financial time series forecasting (Plakandaras et al., 2015; Lin et al., 2012; Yu et al., 2009).

Previous studies have shown that ANN technique and SVR technique are the most commonly used models both individual model forecasting and multiscale decomposition ensemble approach forecasting, indicating that ANN technique and SVR technique are indeed appropriate for forecasting exchange rates. If we combine the advantages of these two techniques, we can get better predictive performance. Support vector neural network (SVNN) technique is an artificial neural network with similar properties of SVR technique. Therefore, it supports better alternatives for forecasting exchange rates. In addition, the above-mentioned ensemble learning approaches generally select empirical mode decomposition (EMD) method or ensemble empirical mode decomposition (EEMD) method to decompose the raw time series. Since the decomposition strategy is very important for ensemble learning approaches, a better decomposition algorithm may enhance the forecasting performance. Previous studies have confirmed that variational mode decomposition (VMD) method is a more efficient decomposition algorithm than EMD and EEMD. Hence, VMD method is used for exchange rates series decomposition in this study.

Due to the high volatility and irregularity nature of foreign exchange rates, the "decomposition and ensemble" principle is especially used to deal with the difficulties in modeling and forecasting foreign exchange rates. Accordingly, this study proposes a new multiscale decomposition ensemble approach integrating variational mode decomposition (VMD) method and support vector neural network (SVNN) technique to forecast EUR, GBP, JPY, CNY against USD daily foreign exchange rates. Our proposed approach is called VMD-based SVNN multiscale decomposition ensemble approach, *i.e.*, VMD-SVNN-SVNN multiscale decomposition ensemble approach. Firstly, in the proposed multiscale decomposition ensemble approach, variational mode decomposition (VMD) method, which is an efficient decomposition method relative to some others (e.g., EMD and wavelet decomposition), is employed to divide the original foreign exchange rates data into a finite number of relatively independent subcomponents. Secondly, SVNN, a fast and powerful neural network relative to traditional statistical models and other AI techniques (e.g., MLPNN and SVM techniques), is used to forecast the different subcomponents respectively. Finally, these forecasted subcomponents are fused into an ensemble result as the final forecasting by another SVNN ensemble learning method.

The main contribution of this study is to propose a new multiscale decomposition ensemble approach to improve the forecasting performance of the EUR, GBP, JPY, and CNY against USD daily foreign exchange rates, and to compare its forecasting performance with some other existing forecasting techniques in terms of level accuracy, directional accuracy, and statistical tests. Different from the other existing multiscale decomposition ensemble approaches, the proposed approach has many features: Firstly, VMD is used as decomposition tool to decompose the complex and irregular exchange rate data into multiscale subcomponents. The decomposed subcomponents capture the fluctuations caused by extreme events or other factors (Zhang et al., 2009). VMD can take advantage of the "decomposition and ensemble" principle as well as decrease the computational cost when decomposing the original data; Secondly, SVNN technique is utilized as the individual forecasting and ensemble learning tool, taking advantage of its powerful forecasting capability, timesaving training process and model robustness.

The rest of this study is organized as follows. Section 2 reviews the literature related to exchange rate forecasting. Section 3 introduces related methods and the formulation process of our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach in detail. Empirical results and performance of our proposed approach are discussed in Section 4. Finally, some concluding remarks and future work are drawn in Section 5.

2. Literature review

Exchange rates forecasting is often considered as one of the most challenging problems in financial time series forecasting due to its high volatility, nonlinearity, complexity and noisiness. How to accurately forecast the exchange rates movement is still an open question with respect to the economic and social organization of modern society. To tackle this challenge, a lot of research work has been devoted to exploring the high volatility, nonlinearity, complexity and noisiness nature of foreign exchange rates and to developing specific nonlinear approaches to improve performance of exchange rate forecasting. These forecasting approaches can be divided into three major categories: single forecasting models, hybrid forecasting approaches, ensemble learning and combination forecasting approaches. Each family of the above approaches is detailed as follows.

Firstly, in a variety of single forecasting models, many prototypes of different methods have been proposed for forecasting foreign exchange rates, such as autoregressive integrated moving average (ARIMA) model (Xiong et al., 2017; Chortareas et al., 2011), generalized autoregressive conditional heteroscedasticity (GARCH) model (West and Cho, 1995; Chortareas et al., 2011), vector auto-regression model (VAR) (Joseph, 2001; Carriero et al., 2009), co-integration model (Moosa and Vaz, 2016; McCrae et al., 2002) and error correction model (ECM) (Moosa and Vaz, 2016). Nevertheless, some advanced artificial intelligence (AI) techniques have been proposed for forecasting exchange rates, such as support vector regression (SVR) (Huang et al., 2010), artificial neural networks (ANNs) (Özkan, 2013; Kuan and Liu, 1995; Zhang and Hu, 1998) and deep learning techniques (Shen et al., 2015). In these research works, Joseph (2001) used vector autoregression model to study daily, weekly and monthly CHF, DEM, ERE, GBP, ITL, NLG against USD exchange rates. McCrae et al. (2002) employed the ARIMA model with error correction to forecast daily JPY, MY, PHP, THB, SGD against USD. Zhang and Hu (1998) applied the artificial neural network to forecast daily and weekly GBP/USD exchange rate. Hu et al. (1999) found that the multilayer perceptron neural network is better than random work model in forecasting monthly GBP/USD exchange rate. Leung et al. (2000) developed a new general regression neural network to forecast the monthly GBP, CAD, JPY against USD. Shen et al. (2015) used several deep learning algorithms, such as deep belief network, continuous restricted Boltzmann machines and conjugate gradient method to forecast weekly GBP, BRL, INR against USD exchange rates.

Secondly, numerous hybrid approaches have been applied to forecast foreign exchange rates in the family of hybrid forecasting approaches. These approaches mainly consist of three parts: data preprocessing, forecasting model formulation, and parameters optimization. Examples of such approaches include Bayesian models with shrinkages techniques (Wright, 2008), rolling genetic algorithm-based SVR (Sermpinis et al., 2015), Kalman filter combined with artificial neural networks (Sermpinis et al., 2012), adaptive radial basis functions neural network optimized by particle swarm optimization algorithm (Sermpinis et al., 2013), machine learning models combined with decomposition algorithms and variable selection methods (Plakandaras et al., 2015), recurrent, higher order and Psi sigma neural networks with confirmation filter leverages (Dunis et al., 2011), dynamic stochastic general equilibrium (DSGE) models combined with Bayesian vector autoregressive (Zorzi et al., 2017), and improved ant colony optimization-based SVR (Hung and Hong, 2009). In these previous studies, Sermpinis et al. (2015) found that SVR optimized by rolling genetic algorithm is more accurate than other benchmark models in forecasting and trading daily exchange rates between the USD and three other major currencies - EUR, GBP and JPY. Sermpinis et al. (2012)

applied artificial neural networks with Kalman filter to forecast and trade the daily EUR/USD exchange rate. Sermpinis et al. (2013) developed adaptive radial basis functions neural network optimized by particle swarm optimization algorithm to find the best neural network configuration to forecast and trade daily USD, GBP and JPY against EUR. Other previous studies utilizing hybrid approaches in exchange rates forecasting include Clarida et al. (2003) and Zhang (2003).

Thirdly, ensemble learning and combination approaches have been demonstrated to obtain better performance than single forecasting models and some hybrid forecasting approaches in foreign exchange rates forecasting. Ensemble learning and combination approaches include week forecasters and ensemble strategies. Examples of such approaches include clustering-based nonlinear ensemble learning approach (Sun et al., 2018), time-varying weights combination forecasting approach (Kouwenberg et al., 2013), Bootstrap-based Kitchen-sink regression approach (Ribeiro, 2017), decomposition and ensemble with variable selection learning approach (Plakandaras et al., 2015) and neural network-based ensemble learning approach (Zhang and Berardi, 2001). In these ensemble learning and combination forecasting approaches studies, Sun et al. (2018) originally proposed a novel clustering-based nonlinear ensemble learning approach to forecast daily and monthly EUR, GBP, JPY and CNY against USD, the empirical results indicate that the forecasting performance of the clustering-based nonlinear ensemble approach is far superior to other benchmarks used in this study. Yu et al. (2009) used NN-based nonlinear meta-learning approach to design a system of financial time series forecasting. Kouwenberg et al. (2013) employed a novel time-varying weights combination forecasting approach to find the best combination weights for forecasting quarterly CAD, AUD, NZD, BRL, JPY, MXN,/NOK, RUB, CHK and GBP against USD foreign exchange rates. Other previous studies utilizing ensemble learning and combination approaches for exchange rates forecasting include Yu et al. (2005) and Yu et al. (2008).

3. Related methodologies

This section develops a new VMD-SVNN-SVNN multiscale decomposition ensemble approach to forecast exchange rates. Decomposition approach VMD and ensemble approach SVNN are presented in Sections 3.1 and 3.2, respectively. Finally, the overall process of our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is shown in Section 3.3.

3.1. Variational mode decomposition

Variational mode decomposition (VMD) proposed by Dragomiretskiy and Zosso (2014) is a novel and effective non-recursive signal processing algorithm. The main work of VMD is to decompose original time series f into k discrete number of band-limited modes, where each mode is required to compact around a center pulsation ω_k which is determined during the decomposition process.

For example, the original signal series f is decomposed into a set of modes μ_k around a center pulsation ω_k by means of the following constrained variational problem:

$$\min_{\mu_k,\omega_k} \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * \mu_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \tag{1}$$

Subject to:

$$\sum_k \mu_k = f \tag{2}$$

where k is number of modes, δ denotes the Dirac distribution, t is time script, and * is convolution operator.

The constrained variational optimization above can be solved by an unconstrained optimization problem in terms of a quadratic penalty term and Lagrange multipliers, which can be presented as follows:

$$L(\mu_k,\omega_k,\lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * \mu_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_k \mu_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k \mu_k(t) \right\rangle \tag{3}$$

where λ is Lagrange multipliers, α is a balance parameter of the data-fidelity constraint, and $\left\| f(t) - \sum_k \mu_k(t) \right\|_2^2$ represents a quadratic penalty term for accelerating the rate of convergence.

Then the Eq. (3) is addressed by optimization algorithm of the alternate direction method of multipliers (ADMM) by finding the saddle point of the augmented Lagrangian L in a sequence of iterative sub-optimizations. Consequently, the solutions for μ_k, ω_k and λ can be expressed as follows:

$$\widehat{\mu}_k^{n+1}(\omega) = \frac{\widehat{f}(\omega) - \sum_{i\neq k}\widehat{\mu}_i(\omega) + \frac{\widehat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega-\omega_k)^2} \tag{4}$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\widehat{\mu}_k(\omega)|^2 d\omega}{\int_0^\infty |\widehat{\mu}_k(\omega)|^2 d\omega} \tag{5}$$

$$\widehat{\lambda}^{n+1}(\omega) = \widehat{\lambda}^{n}(\omega) + \tau \left(\widehat{f}(\omega) - \sum_k \widehat{\mu}_k^{n+1}(\omega) \right) \tag{6}$$

where $\widehat{f}(\omega)$, $\widehat{\mu}_i(\omega)$, $\widehat{\lambda}(\omega)$, $\widehat{\lambda}^n(\omega)$ and $\widehat{\mu}_k^{n+1}(\omega)$ represent the Fourier transform of $f(\omega)$, $\mu_i(\omega)$, $\lambda(\omega)$, $\lambda^n(\omega)$ and $\mu_k^{n+1}(\omega)$, respectively, and n is the number of iterations. For further details on VMD algorithm, please refer to Dragomiretskiy and Zosso (2014).

In the VMD framework, the mode μ with high order k represents low frequency components. Before VMD method, the number of modes k should be predetermined. In this study, to address this problem regarding optimal selection of the parameter k. A mode number fluctuation method is proposed to determine the number of modes k. The flowchart is displayed in Fig. 1. The detailed process is as follows:

Step 1: the initial value of mode number is $k = k_0$.
Step 2: when the number of modes is k_0, determine whether the central frequencies of mode overlap.
Step 3: if the central frequencies of mode overlap, decrease the mode number and perform VMD until the central frequencies do not overlap. Return k.
Step 4: if the central frequencies of mode do not overlap, increase the mode number and perform VMD until the central frequencies overlap. Return $k-1$.

3.2. Support vector neural network

Support vector neural network (SVNN) is an extension of support vector regression (SVR). It is selected as the individual forecasting and ensemble learning tool in this study. For illustration, this subsection first introduces the SVR technique, and then presents the SVNN technique.

3.2.1. Support vector regression

Support vector regression (SVR) is an extension of support vector machine (SVM), SVR is a non-linear regression method by means of the principle of structural risk minimization and it can well capture the non-linear patterns hidden in the raw data. The main work of SVR is to map input data x into the high dimensional feature space F using a nonlinear function ϕ, and then to perform linear regression in the feature space F.

If we introduce two slack variables ξ_i and ξ_i^* that correspond to the distance of the actual values from the corresponding boundary values of

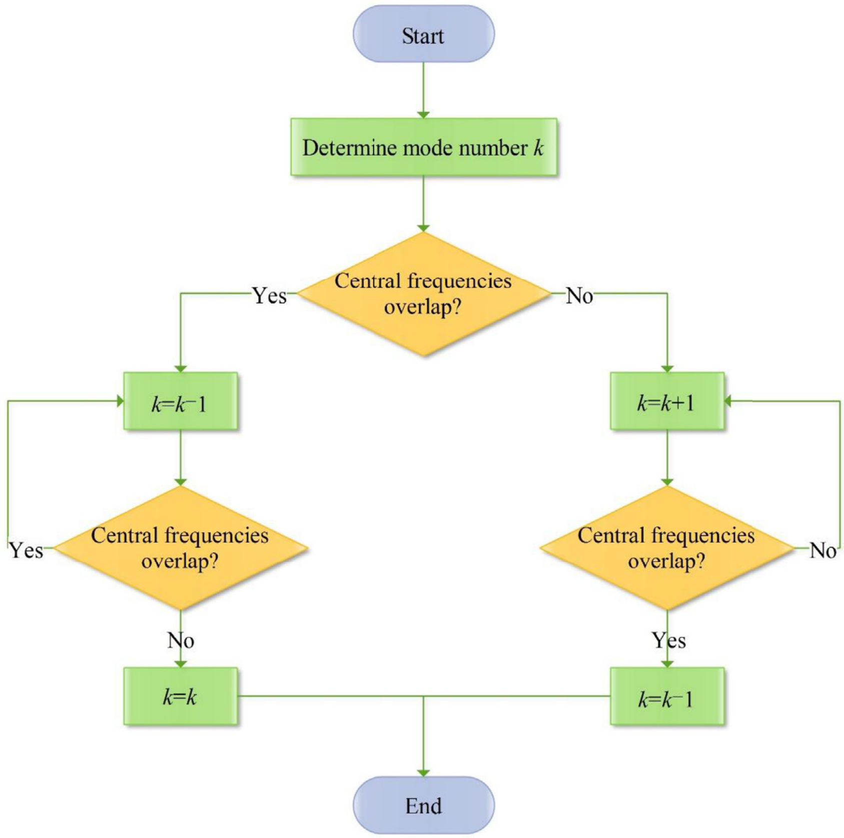

Fig. 1. The flowchart of estimating the mode number k of VMD.

the ε-insensitive loss function, then SVR can be transformed to the following argument:

$$\begin{cases} \min & C\sum_{i=1}^{n}(\xi_i+\xi_i^*)+\frac{1}{2}\|\omega\|^2 \\ & \hat{y}_i - y_i \le \varepsilon + \xi_i \\ s.t. & y_i - \hat{y}_i \le \varepsilon + \xi_i^* \\ & \xi_i \ge 0, \xi_i^* \ge 0, C > 0 \end{cases} \tag{7}$$

where ε is a predefined parameter, C is a regularized constant, and $\hat{y}_i = \omega^T\phi(x_i) + b$. The term $\sum_{i=1}^{n}(\xi_i+\xi_i^*)$ is the error of in-sample dataset. This optimization problem can be transformed into a dual problem that solution is based on the Lagrangian multipliers (α_i and $\hat{\alpha}_i$) and mapping by a kernel function $K(x_i, x)$. Hence, the Eq. (7) can be transformed as follows:

$$\hat{y}_i = \sum_{i=1}^{n}(\hat{\alpha}_i - \alpha_i)K(x_i, x) + b \tag{8}$$

Factor b is estimated by the Karush-Kuhn-Tucker conditions (for a detail mathematical derivation, please refer to Vapnik, 1995). In this study, the radial basis kernel function is as follows:

$$K(x_i, x) = \exp\left(-\gamma\|x_i - x\|^2\right), \gamma > 0 \tag{9}$$

3.2.2. Support vector neural network

Support vector neural network (SVNN) introduced by Ludwig et al. (2014) is a special kind of single-hidden layer feedforward neural network (SLFN) and employs eigenvalue decay as regularization term. The main work of SVNN is to introduce eigenvalue decay algorithm for maximum margin training that is based on regularization and evolutionary computing.

The formulation of SLFN is expressed as follows:

$$y_h = \varphi(W_1 \cdot x + b_1) \tag{10}$$

$$\hat{y} = W_2^T \cdot y_h + b_2 \tag{11}$$

where y_h denotes the outputs of hidden layer, x is the input vector, W_1 represents the weights matrix from the input layer to the hidden layer, W_2 represents the weights matrix from the hidden layer to the output layer, b_1 denotes the bias of the hidden layer, b_2 denotes the bias vector of the output layer, and $\varphi(\cdot)$ represents the sigmoid function.

The objective function of SLFN is evaluated by the mean squared error (MSE) of in-sample dataset:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{12}$$

where n is the number of in-sample dataset, y_i and $\hat{y}_i$ represent the target output and the predicted output, respectively.

In SVNN method, the main purpose of eigenvalue-decay is to establish a relationship between the eigenvalue minimization and the classification margin. The objective function of eigenvalue-decay is expressed by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 + \kappa(\lambda_{\min} + \lambda_{\max}) \tag{13}$$

where κ is regularization hyperparameter, $\lambda_{\min}$ is minimum eigenvalue of $W_1W_1^T$, $\lambda_{\min}$ is maximum eigenvalue of $W_1W_1^T$.

The SVNN method can be considered by solving the similar optimization problem as follows:

$$\begin{cases} \min & C\sum_{i=1}^{n}(\xi_i+\xi_i^*)+(\lambda_{\min}+\lambda_{\max}) \\ & \widehat{y}_i-y_i\le\varepsilon+\xi_i \\ s.t. & y_i-\widehat{y}_i\le\varepsilon+\xi_i^* \\ & \xi_i\ge 0,\xi_i^*\ge 0, C>0. \end{cases} \tag{14}$$

where $\widehat{y}_i = W_2^T\varphi(W_1\cdot x_i+b_1)+b_2$, y_i is the target output, ε is a predetermined parameter, C is a regularization hyperparameter, ξ_i and ξ_i^* are two non-negative slack variables. For a detail mathematical derivation on SVNN method, please refer to Ludwig et al. (2014).

3.3. Overall process of the VMD-SVNN-SVNN multiscale decomposition ensemble approach

In this study, the h-step-ahead forecasting horizons are used to assess the superiority of our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach. Given a time series $y_t, (t=1,2,\cdots,n)$, the h-step-ahead forecasting for $\widehat{y}_{t+h}$ is as follows:

$$\widehat{y}_{t+h}=f\left(y_t,y_{t-1},\ldots,y_{t-(l-1)}\right) \tag{15}$$

where $\widehat{y}_{t+h}$ is the h-step-ahead forecasted value at time t, y_t is the actual value at time t, and l denotes the lag orders selected by autocorrelation and partial correlation analysis.

The framework of our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is displayed in Fig. 2, which mainly consists of four main parts:

1) A mode number fluctuation algorithm is used to determine the number k of modes.
2) The raw foreign exchange rate data $\{y_1,y_2,\ldots,y_n\}$ is decomposed into k modes via VMD method.
3) Each mode is forecasted using SVNN neural network independently.
4) The forecasting results of each mode are fused to generate a final forecasting results $\widehat{y}_t$, using another SVNN neural network as an ensemble method.

4. Empirical study

4.1. Datasets and performance evaluation criteria

This study collects four foreign exchange rates time series as case study from the Wind Database (http://www.wind.com.cn/), namely US dollar (USD) against Euro (EUR), Chinese yuan (CNY), British Pound (GBP) and Japanese Yen (JPY). All series are covering daily data covering the period from January 1, 2011 to May 31, 2017, excluding weekends and holidays. For modeling and validation purposes, the datasets are divided into two parts. It is provided in Table 1.

The descriptive statistics of four foreign exchange rates are provided in Appendix A. To assess the forecasting accuracy of our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach form different perspectives, such as level forecasting and directional forecasting, two main indictors including mean absolute percentage error (MAPE) and directional symmetry (DS) are selected as follows:

$$MAPE=\frac{1}{N}\sum_{t=1}^{N}\left|\frac{y(t)-\widehat{y}(t)}{y(t)}\right|\times 100\% \tag{16}$$

$$DS=\frac{1}{N}\sum_{t=1}^{N}d(t)\times 100\%,\quad d(t) =\begin{cases}1 & if \quad [y(t+1)-y(t)][\widehat{y}(t+1)-y(t)]\ge 0\\ 0 & otherwise\end{cases} \tag{17}$$

where $\widehat{y}(t)$ and $y(t)$ denote the forecasted value and the actual value, respectively, and N is the size of observations.

To evaluate the forecasting performance of our proposed approach from a statistical perspective, two tests including the Diebold-Mariano (DM) (Diebold and Mariano, 2002; Sun et al., 2017) and Pesaran-Timmermann (PT) (Pesaran and Timmermann, 1992; Sun et al., 2017) are performed. The DM test aims to check the null hypothesis of equality of expected forecast accuracy against the alternative of different forecasting abilities across models. In this study, the mean square error (MSE) and mean absolute error (MAE) are used as the DM loss function, and our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is compared against each other benchmark model under study. The PT test is used to examine whether the directional changes of the actual and forecasted values are in step with one another. In other words, it checks how well rises and falls in the predicted value follow the real rises and falls of the original time series. The null hypothesis is that the model under study has no power on forecasting the foreign exchange rates. For a detail mathematical derivation on DM and PT statistic tests, please refer to Diebold and Mariano (2002), Pesaran and Timmermann (1992).

4.2. Empirical results

To evaluate the out-of-sample forecasting accuracy of our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach, four single models including RW, ARIMA, SVR, SVNN and seven multiscale decomposition ensemble approaches including EEMD-SVR-ADD, EEMD-SVNN-ADD, EEMD-SVR-SVR, EEMD-SVNN-SVNN, VMD-SVR-ADD, VMD-SVNN-ADD and VMD-SVR-SVR were accomplished on four major foreign exchange rate datasets for model evaluation and model comparison. This study employs autocorrelation function (ACF) and partial correlation function (PCF) to determine the input nodes of SVR and SVNN methods, and the hidden nodes of SVNN were determined by means of the trial-and-error method. The output node of SVR and SVNN methods is set to one. The parameter of ARIMA model is estimated by an automatic model selection algorithm accomplished using the "forecast" program package in the R software. Other methods are implemented using Matlab 2016a software.

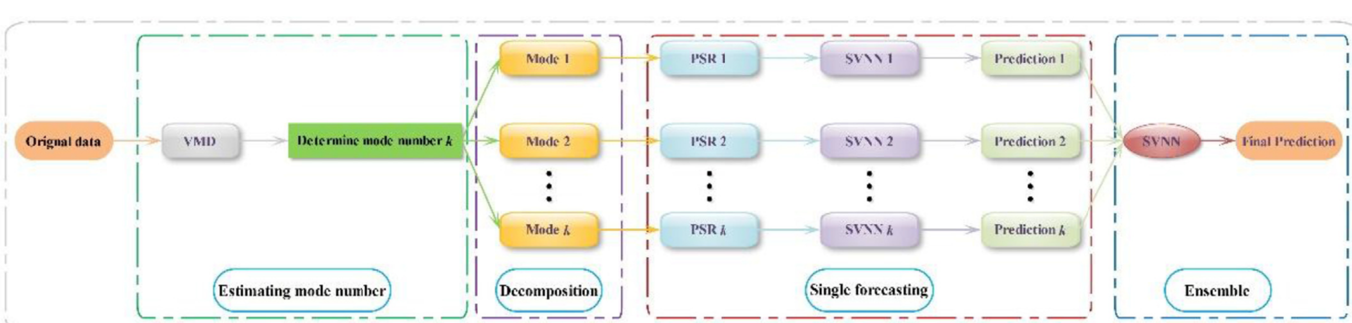

Fig. 2. The overall process of the VMD-SVNN-SVNN multiscale decomposition ensemble approach.

Table 1
In-sample and out-of-sample datasets of four foreign exchange rates data.

Exchange rates	in-sample			out-of-sample		
	from	to	size of samples	from	to	size of samples
EUR/USD	2011.01.03	2016.02.29	1341	2016.03.01	2017.05.31	327
USD/CNY	2011.01.04	2016.02.29	1248	2016.03.01	2017.05.31	305
GBP/USD	2011.01.03	2016.02.29	1341	2016.03.01	2017.05.31	327
USD/JPY	2011.01.03	2016.02.29	1341	2016.03.01	2017.05.31	327

4.2.1. Forecasting performance evaluation

This section discusses the forecasting accuracy of between single models and multiscale decomposition ensemble approaches. Tables 2–4 provide the statistical evaluation results of level forecasting accuracy (MAPE) and directional forecasting accuracy (DS). We can see from Tables 2–4 that the out-of-sample forecasting accuracy of our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is better than that of the single models and all other multiscale decomposition ensemble approaches throughout the four exchange rates data. This means that our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is a powerful and effective framework to predict exchange rates.

Tables 2–4 illustrate that our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach significantly outperforms all other benchmarks in terms of level accuracy and directional accuracy for four foreign exchange rates forecasting. It is worth noting that all multiscale decomposition ensemble approaches obviously outperform the single models, while single SVR and SVNN consistently outperform RW and ARIMA in terms of level accuracy and directional accuracy. In other words, our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is 13.45–23.25% more accurate than RW model in directional forecasts, reaching up to hit a rate of 73.09% in out-of-sample directional forecasting accuracy for the EUR/USD in one-step-ahead forecasting.

Several important conclusions can be drawn from performance comparison above: (1) Our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is generally the best performing model in comparing with the other benchmarks used in this study for exchange rates forecasting in terms of MAPE and DS criteria; (2) The multiscale decomposition ensemble approaches generally outperforms the single models according to the comparison results above. This indicate that decomposition of time series using the EEMD and VMD algorithm prior to forecasting can significantly improve the forecasting performance of exchange rates; (3) The VMD-based multiscale decomposition ensemble approach is generally much better than the EEMD-based multiscale decomposition ensemble approach. This indicate that VMD is a more effective decomposition algorithm; (4) Due to the high volatility and nonlinear patterns in the time series of exchange rates, nonlinear models are more suitable for forecasting exchange rates than the traditional linear models; (5) Our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is a promising method for time series forecasting with high volatility.

4.2.2. Statistical tests

The DM statistic is the null hypothesis of equal forecasting accuracy between two forecasts. In this study, the mean squared error (MSE) and mean absolute error (MAE) are considered as DM loss functions. The tests are applied in the four out-of-sample periods. Table 5 and Appendix B1 and B2 present the DM statistics comparing the VMD-SVNN-SVNN multiscale decomposition ensemble approach with its benchmarks for three forecasting horizons.

From Table 5 and Appendix B1 and B2, it is clear that all the DM statistics from the VMD-SVNN-SVNN multiscale ensemble approach tests are less than -1.8839, which corresponds to p-values are less than 0.03. This indicates that the VMD-SVNN-SVNN multiscale decomposition ensemble approach significantly outperforms some other benchmark models for one-step-ahead forecasting scheme under the 97% confidence level.

From the DM statistic and p-values, the test results indicate that: (1) While the VMD-SVNN-SVNN multiscale decomposition ensemble approach is regarded as the tested method, all the p-values are less than 0.03. It is revealed that the new approach is far superior to the other benchmark models at the three sites under the 97% confidence level. (2) The forecasting performance of the VMD-SVR-SVR multiscale decomposition ensemble approach and the EEMD-SVNN-SVNN multiscale decomposition ensemble approach are quite similar and neither of them can statistically outperform the other; (3) The VMD-SVNN-SVNN multiscale decomposition ensemble approach is better than EEMD-SVNN-SVNN multiscale decomposition ensemble approach and EEMD-SVR-SVR multiscale decomposition ensemble approach under the 95% confidence level, which indicates a high decomposition performance for the VMD algorithm; (4) The SVNN model and SVR model outperform the econometric models under the 99% confidence level. Thus, the AI-based models are efficient to forecast exchange rates; (5) The ARIMA and RW are the worst performing models under the one-step-ahead forecasting scheme.

To further verify the statistical superiority of our proposed approach, the PT statistic for directional accuracy is calculated. The PT statistic is employed to examine whether the directional movements of the actual and forecast values are the same. In other words, it checks how well the

Table 2
Performance comparison of different models for different exchange rates: one-step-ahead forecasting results.

Models	EUR/USD		USD/CNY		GBP/USD		USD/JPY	
	MAPE	DS	MAPE	DS	MAPE	DS	MAPE	DS
RW	0.664	50.46	0.514	49.18	0.874	48.62	0.947	48.93
ARIMA	0.619	49.24	0.492	48.20	0.813	50.15	0.892	51.07
SVR	0.498	56.57	0.341	50.49	0.696	53.52	0.697	56.27
SVNN	0.417	58.10	0.307	51.15	0.617	57.49	0.626	56.88
EEMD-SVR-ADD	0.402	59.63	0.291	52.13	0.572	58.72	0.584	58.10
EEMD-SVNN-ADD	0.379	61.16	0.284	53.11	0.514	60.86	0.542	59.02
EEMD-SVR-SVR	0.376	61.77	0.287	52.46	0.504	60.24	0.501	60.86
EEMD-SVNN-SVNN	0.319	63.61	0.269	56.07	0.485	61.16	0.497	62.39
VMD-SVR-ADD	0.325	66.06	0.249	58.69	0.423	61.47	0.507	64.83
VMD-SVNN-ADD	0.296	69.72	0.224	60.98	0.406	64.53	0.473	67.28
VMD-SVR-SVR	0.274	70.03	0.213	61.97	0.367	68.50	0.487	67.58
VMD-SVNN-SVNN	0.227	73.09	0.187	64.92	0.304	71.87	0.411	70.64

Table 3
Performance comparison of different models for different exchange rates: three-step-ahead forecasting results.

Models	EUR/USD		USD/CNY		GBP/USD		USD/JPY	
	MAPE	DS	MAPE	DS	MAPE	DS	MAPE	DS
RW	1.682	47.09	1.046	45.90	1.704	46.79	1.876	45.87
ARIMA	1.597	46.79	0.997	48.52	1.576	47.71	1.757	48.32
SVR	1.471	51.68	0.754	50.82	1.485	52.29	1.432	54.74
SVNN	1.387	54.13	0.702	52.46	1.249	55.35	1.397	50.15
EEMD-SVR-ADD	1.226	53.82	0.635	55.43	1.219	55.66	1.305	52.60
EEMD-SVNN-ADD	1.035	54.43	0.584	56.07	1.173	55.05	1.169	54.74
EEMD-SVR-SVR	1.149	54.74	0.591	57.38	1.167	56.57	1.269	56.57
EEMD-SVNN-SVNN	0.978	56.57	0.553	59.02	1.013	55.35	1.035	55.65
VMD-SVR-ADD	0.894	57.19	0.512	60.00	0.984	56.88	0.984	56.57
VMD-SVNN-ADD	0.841	58.41	0.468	60.98	0.911	58.41	0.903	58.10
VMD-SVR-SVR	0.816	58.10	0.461	61.31	0.927	57.80	0.927	57.80
VMD-SVNN-SVNN	0.701	60.55	0.398	63.93	0.784	61.47	0.804	59.63

Table 4
Performance comparison of different models for different exchange rates: six-step-ahead forecasting results.

Models	EUR/USD		USD/CNY		GBP/USD		USD/JPY	
	MAPE	DS	MAPE	DS	MAPE	DS	MAPE	DS
RW	3.991	45.87	1.459	45.24	4.021	47.09	3.571	45.57
ARIMA	3.874	47.09	1.354	46.23	3.917	47.40	3.049	44.64
SVR	3.049	51.99	1.176	49.84	3.025	55.96	2.465	49.54
SVNN	2.964	53.82	1.147	52.13	2.769	55.66	2.043	50.46
EEMD-SVR-ADD	3.053	57.74	1.119	53.11	2.437	55.96	1.958	51.68
EEMD-SVNN-ADD	2.974	55.05	0.963	55.08	2.206	57.49	1.841	52.91
EEMD-SVR-SVR	2.987	55.35	0.972	56.07	2.273	57.19	1.892	55.97
EEMD-SVNN-SVNN	2.742	55.96	0.947	57.70	2.156	56.27	1.739	56.88
VMD-SVR-ADD	2.651	56.57	0.902	58.69	1.785	56.88	1.628	57.19
VMD-SVNN-ADD	2.334	57.80	0.832	59.67	1.467	58.41	1.367	57.80
VMD-SVR-SVR	2.138	57.80	0.841	60.00	1.491	58.10	1.468	58.10
VMD-SVNN-SVNN	2.014	59.94	0.716	61.97	1.214	60.55	1.225	59.02

Table 5
DM statistics for MSE and MAE loss functions: one-step-ahead forecasting.

Models	EUR/USD		USD/CNY		GBP/USD		USD/JPY	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
RW	−4.01***	−3.89***	−3.94***	−3.88***	−3.96***	−3.88***	−3.90***	−3.98***
ARIMA	−3.75***	−3.52***	−3.81***	−3.67***	−3.83***	−3.63***	−3.80***	−3.74***
SVR	−2.91***	−2.86***	−2.98***	−2.83***	−2.88***	−2.95***	−2.88***	−2.93***
SVNN	−2.91***	−2.71***	−2.17**	−2.40***	−2.01**	−2.17**	−2.22**	−2.29**
EEMD-SVR-ADD	−2.46***	−2.34***	−2.26**	−2.33***	−2.16**	−2.29**	−2.16**	−2.04**
EEMD-SVNN-ADD	−2.35***	−2.28**	−2.22**	−2.25**	−2.24**	−2.31**	−2.09**	−2.11**
EEMD-SVR-SVR	−2.20**	−2.11**	−2.21**	−2.17**	−2.20**	−2.12**	−2.03**	−1.97**
EEMD-SVNN-SVNN	−1.98**	−2.02**	−1.98**	−2.01**	−1.92**	−2.03**	−1.96**	−2.01**
VMD-SVR-ADD	−2.08**	−1.89**	−1.95**	−2.06**	−1.84**	−1.98**	−1.90**	−1.92**
VMD-SVNN-ADD	−2.03**	−1.84**	−1.87**	−1.93**	−1.93**	−1.96**	−1.84**	−1.73**
VMD-SVR-SVR	−1.97**	−1.62*	−1.71**	−1.85**	−1.88**	−1.74**	−1.89**	−1.63*

Note: The table reports the DM test values. * denotes a rejection of null hypothesis at the 10% significance level. ** denotes a rejection of null hypothesis at the 5% significance level. *** denotes a rejection of null hypothesis at the 1% significance level.

volatility of the forecasted values follows the real volatility of exchange rate series. The null hypothesis assumes model under study has no power on forecasting the relevant exchange rates return series. The results of out-of-sample PT statistic for four exchange rates are provided in Table 6 and Appendix C1 and C2.

The results of Table 6 and Appendix C1 and C2 show that our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach displays the best statistical performance for each exchange rate series. The PT statistics reject the null hypothesis under 99% confidence level for all exchange rates series and forecasting horizons under study. Therefore, our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach can be used to forecast directional movements of exchange rates effectively. The forecasting performance of VMD-SVR-SVR multiscale decomposition ensemble approach also rejects the null hypothesis under 99% confidence level for all exchange rates series and forecasting horizons under study. All other single benchmarks are almost ineffective since their p-values are greater than 0.1 for all series and forecasting horizons.

According to the results of the statistical tests, the forecasting power of our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is verified with statistical evidence.

4.3. Summary

In summary, five conclusions can be drawn from the empirical results presented in Section 4.2: (1) The forecasting performance of SVNN is the best among single models. (2) The multiscale decomposition ensemble approaches outperform the single benchmark models. (3) VMD as a decomposition method is effective in improving the forecasting accuracy and stability of single benchmark models. (4) The superiority of our

Table 6
PT statistics results: one-step-ahead forecasting.

Models	EUR/USD	USD/CNY	GBP/USD	USD/JPY
RW	0.1539	−0.1238	−0.0987	0.1016
ARIMA	0.2143	0.1843	−0.5139	−0.3127
SVR	−0.4417	−0.3192	0.3917	0.4561
SVNN	1.0134	1.1457	1.3067	1.4438
EEMD-SVR-ADD	1.6637*	1.7049*	1.5637	1.6034
EEMD-SVNN-ADD	1.7033*	1.7536*	1.6721*	1.6442
EEMD-SVR-SVR	2.2604**	1.9168*	2.1635**	2.0143**
EEMD-SVNN-SVNN	2.6583***	2.5033**	2.3419**	2.4017**
VMD-SVR-ADD	2.6014***	2.7038***	2.4513**	2.6137***
VMD-SVNN-ADD	2.7517***	2.8341***	2.7016***	2.8104***
VMD-SVR-SVR	3.0612***	3.2027***	3.0018***	2.9425***
VMD-SVNN-SVNN	3.4605***	3.6971***	3.5021***	3.4954***

Note: The table reports the values of the PT statistics. * denotes a rejection of null hypothesis at the 10% significance level. ** denotes a rejection of null hypothesis at the 5% significance level. *** denotes a rejection of null hypothesis at the 1% significance level.

proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is verified by statistical tests. (5) Our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach can be considered as a promising solution for exchange rates forecasting with high volatility.

The proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach can obtain better forecasting performance mainly due to several reasons. Firstly, the foreign exchange rates are affected by many factors. VMD is utilized in the proposed approach to decompose the complex and irregular exchange rate data into multiscale subcomponents. The decomposed subcomponents capture the fluctuations caused by extreme events or some other factors (Zhang et al., 2009). VMD can take advantage of the “decomposition and ensemble” principle as well as decrease the computational cost when decomposing the original data. Secondly, SVNN is more suitable to deal with the nonlinearity and non-stationary data. It is used to forecast the subcomponents with different frequencies separately, which can obtain more information than the original data. Thirdly, another SVNN is used to integrate the forecasting results of all the subcomponents, which can determine the weights scientifically and automatically to obtain better forecasting performance.

5. Conclusions and future work

In this study, the VMD-SVNN-SVNN multiscale decomposition ensemble approach based on the “decomposition and ensemble” principle is proposed for foreign exchange rate forecasting. The main ideas of our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach are as follows: 1) The original exchange rate series is decomposed into subcomponents using VMD method. 2) The extracted subcomponents are modeled independently using SVNN technique as single forecasting model. 3) The forecasting results of each subcomponents are combined to generate final forecasting results using another SVNN technique as an ensemble learning tool. To illustrate and verify the forecasting performance of our proposed approach, we compare its forecasting accuracy with other benchmark models with respect to the USD and four other major currencies - EUR, GBP, CNY and JPY. The experimental results show that our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach can significantly enhance the forecasting performance and statistically outperform some other popular forecasting methods in terms of directional forecasting accuracy, level forecasting accuracy and statistical tests. This indicates that our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach is a promising solution for forecasting foreign exchange rates.

Besides foreign exchange rate forecasting, our proposed VMD-SVNN-SVNN multiscale decomposition ensemble approach can be applied to solve other complex and difficult forecasting issues, including stock index forecasting, crude oil price forecasting, container throughput forecasting and traffic flow forecasting.

At the same time, this study has some limitations since it only focuses on univariate time series analysis without taking other factors affecting foreign exchange rate into consideration. If those factors can be integrated into our proposed approach, the forecasting performance may be improved. In addition, the kernel function of SVNN and SVR is selected only based on the experience, which may not be optimal for the specific problem. Hence, the optimal selection of kernel function for the specific problem is left for a later study.

Conflicts of interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgement

This research is supported by the National Natural Science Foundation of China (Project No: 71801213 and 71642006). Authors would like to express their sincere appreciation to the editors and the two anonymous referees for making valuable comments and suggestions to this paper. Their comments and suggestions have improved the quality of the paper immensely.

Appendix A. Descriptive statistics

Time series	Maximum	Minimum	Mean	Std.*	Skewness	Kurtosis
EUR/USD	1.4826	1.0499	1.2831	0.1071	−0.6466	2.3375
USD/CNY	6.6377	6.0412	6.2815	0.1402	0.5420	2.4948
GBP/USD	1.7165	1.3870	1.5811	0.0584	−0.1677	3.0764
USD/JPY	125.5800	75.8100	97.4275	16.3341	0.2123	1.6253

Note: Std.* refers to the standard deviation.

Appendix B1. Diebold-Mariano statistics for MSE and MAE loss functions for three-step-ahead forecasting

Models	EUR/USD		USD/CNY		GBP/USD		USD/JPY	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
RW	−3.88***	−3.93***	−3.89***	−3.90***	−3.76***	−3.84***	−3.94***	−3.81***
ARIMA	−3.64***	−3.60***	−3.74***	−3.79***	−3.58***	−3.61***	−3.82***	−3.68***
SVR	−2.98***	−2.79***	−2.91***	−2.73***	−2.94***	−2.83***	−2.79***	−2.84***

(continued on next column)

(continued)

Models	EUR/USD		USD/CNY		GBP/USD		USD/JPY	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
SVNN	−2.83***	−2.85***	−2.34***	−2.48***	−2.25**	−2.29**	−2.35***	−2.30**
EEMD-SVR-ADD	−2.40***	−2.29**	−2.22**	−2.41***	−2.19**	−2.11**	−2.23**	−2.16**
EEMD-SVNN-ADD	−2.28**	−2.13**	−2.24**	−2.16**	−2.17**	−2.08**	−2.02**	−2.17**
EEMD-SVR-SVR	−2.11**	−2.02**	−2.13**	−2.14**	−2.06**	−2.16**	−1.98**	−2.03**
EEMD-SVNN-SVNN	−2.03**	−2.06**	−1.88**	−1.97**	−1.95**	−1.96**	−1.91**	−1.95**
VMD-SVR-ADD	−2.14**	−1.91**	−1.81**	−1.99**	−1.93**	−1.98**	−1.86**	−1.91**
VMD-SVNN-ADD	−1.99**	−1.79**	−1.75**	−1.92**	−1.87**	−1.84**	−1.75**	−1.79**
VMD-SVR-SVR	−1.91**	−1.71**	−1.62*	−1.73**	−1.70**	−1.66**	−1.60*	−1.68**

Note: The table reports the DM test values. * denotes a rejection of null hypothesis at the 10% significance level. ** denotes a rejection of null hypothesis at the 5% significance level. *** denotes a rejection of null hypothesis at the 1% significance level.

Appendix B2. Diebold-Mariano statistics for MSE and MAE loss functions for six-step-ahead forecasting

Models	EUR/USD		USD/CNY		GBP/USD		USD/JPY	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
RW	−3.04***	−3.06***	−2.81***	−2.92***	−2.50***	−2.44***	−2.46***	−2.51***
ARIMA	−2.89***	−2.74***	−2.78***	−2.74***	−2.16**	−2.21**	−2.19**	−2.27**
SVR	−2.34***	−2.38***	−2.42***	−2.33***	−2.03**	−2.07**	−2.01**	−2.03**
SVNN	−2.25**	−2.19**	−2.18**	−2.09**	−1.98**	−1.94**	−1.96**	−1.88**
EEMD-SVR-ADD	−2.09**	−2.01**	−2.05**	−2.01**	−1.92**	−1.89**	−1.85**	−1.90**
EEMD-SVNN-ADD	−2.02**	−1.95**	−1.96**	−1.85**	−1.84**	−1.85**	−1.78**	−1.72**
EEMD-SVR-SVR	−1.95**	−1.89**	−1.93**	−1.89**	−1.85**	−1.78**	−1.69**	−1.66**
EEMD-SVNN-SVNN	−1.87**	−1.81**	−1.79**	−1.74**	−1.62*	−1.69**	−1.63*	−1.68**
VMD-SVR-ADD	−1.85**	−1.79**	−1.82**	−1.72**	−1.59*	−1.53*	−1.62*	−1.59*
VMD-SVNN-ADD	−1.78**	−1.63*	−1.69**	−1.73**	−1.49*	−1.43*	−1.56**	−1.54*
VMD-SVR-SVR	−1.60*	−1.54*	−1.50*	−1.52*	−1.43*	−1.36*	−1.49*	−1.45*

Note: The table reports the DM test values. * denotes a rejection of null hypothesis at the 10% significance level. ** denotes a rejection of null hypothesis at the 5% significance level. *** denotes a rejection of null hypothesis at the 1% significance level.

Appendix C1. PT statistics results for three-step-ahead forecasting

Models	EUR/USD	USD/CNY	GBP/USD	USD/JPY
RW	0.1036	0.1139	−0.1049	0.1149
ARIMA	−0.1958	−0.2107	0.4358	−0.3418
SVR	−0.3917	0.3058	0.4537	−0.4317
SVNN	1.1059	0.9981	1.2314	1.3058
EEMD-SVR-ADD	1.6943*	1.6843*	1.6729*	1.6682*
EEMD-SVNN-ADD	1.7145*	1.6911*	1.6925*	1.5933
EEMD-SVR-SVR	2.1033**	1.9569*	2.0397**	1.9638**
EEMD-SVNN-SVNN	2.5842***	2.4803**	2.4391**	2.2674**
VMD-SVR-ADD	2.5934***	2.6941***	2.4416**	2.5983***
VMD-SVNN-ADD	2.7296***	2.7715***	2.6043***	2.6148***
VMD-SVR-SVR	2.9947***	3.1025***	2.9061***	2.8832***
VMD-SVNN-SVNN	3.3041***	3.5043***	3.1374***	3.2064***

Note: The table reports the values of the PT statistics. * denotes a rejection of null hypothesis at the 10% significance level. ** denotes a rejection of null hypothesis at the 5% significance level. *** denotes a rejection of null hypothesis at the 1% significance level.

Appendix C2. PT statistics results for six-step-ahead forecasting

Models	EUR/USD	USD/CNY	GBP/USD	USD/JPY
RW	−0.0953	−0.0943	−0.0837	0.1006
ARIMA	0.1513	−0.1139	0.3121	−0.2958
SVR	−0.2916	0.2816	0.4038	0.3964
SVNN	0.9685	0.9125	1.0256	1.2056
EEMD-SVR-ADD	1.5361	1.5418	1.6137	1.6013
EEMD-SVNN-ADD	1.6043	1.6125	1.6852*	1.5442
EEMD-SVR-SVR	2.0169**	1.9033**	1.9658**	1.9416*
EEMD-SVNN-SVNN	2.2017**	2.3611**	2.3967**	2.0361**
VMD-SVR-ADD	2.2374**	2.4368**	2.4026**	2.3581**
VMD-SVNN-ADD	2.5618**	2.6027***	2.5812***	2.4693**
VMD-SVR-SVR	2.6819***	2.7019***	2.8917***	2.7511***
VMD-SVNN-SVNN	2.9612***	2.8586***	3.0016***	2.8905***

Note: The table reports the values of the PT statistics. * denotes a rejection of null hypothesis at the 10% significance level. ** denotes a rejection of null hypothesis at the 5% significance level. *** denotes a rejection of null hypothesis at the 1% significance level.

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2018.12.013.

References

Bellalah, M., Zouari, S., Levyne, O., 2016. The performance of hybrid models in the assessment of default risk. Econ. Modell. 52, 259–265.
Carriero, A., Kapetanios, G., Marcellino, M., 2009. Forecasting exchange rates with a large Bayesian VAR. Int. J. Forecast. 25 (2), 400–417.
Chen, A., Leung, M.T., 2004. Regression neural network for error correction in foreign exchange forecasting and trading. Comput. Oper. Res. 31 (7), 1049–1068.
Cheng, C.H., Wei, L.Y., Liu, J.W., Chen, T.L., 2013. OWA-based ANFIS model for TAIEX forecasting. Econ. Modell. 30, 442–448.
Chortareas, G., Jiang, Y., Nankervis, J.C., 2011. Forecasting exchange rate volatility using high-frequency data: is the euro different? Int. J. Forecast. 27 (4), 1089–1107.
Clarida, R.H., Sarno, L., Taylor, M.P., Valente, G., 2003. The out-of-sample success of term structure models as exchange rate predictors: a step beyond. J. Int. Econ. 60 (1), 61–83.
Diebold, F.X., Mariano, R.S., 2002. Comparing predictive accuracy. J. Bus. Econ. Stat. 20 (1), 134–144.
Dragomiretskiy, K., Zosso, D., 2014. Variational mode decomposition. IEEE Trans. Signal Process. 62 (3), 531–544.
Dunis, C.L., Laws, J., Sermpinis, G., 2011. Higher order and recurrent neural architectures for trading the EUR/USD exchange rate. Quant. Finance 11 (4), 615–629.
Garratt, A., Mise, E., 2014. Forecasting exchange rates using panel model and model averaging. Econ. Modell. 37, 32–40.
Hung, W.M., Hong, W.C., 2009. Application of SVR with improved ant colony optimization algorithms in exchange rate forecasting. Control Cybern. 38 (3), 863–891.
Huang, S., Chuang, P., Wu, C., Lai, H., 2010. Chaos-based support vector regressions for exchange rate forecasting. Expert Syst. Appl. 37 (12), 8590–8598.
Hu, M., Zhang, G., Jiang, C., Patuwo, B., 1999. A Cross-validation analysis of neural network out-of-sample performance in exchange rate forecasting. Decis. Sci 30 (1), 197–216.
Joseph, N.L., 2001. Model specification and forecasting foreign exchange rates with vector autoregressions. J. Forecast. 20 (7), 451–484.
Kouwenberg, R., Markiewicz, A., Verhoeks, R., Zwinkels, R.C.J., 2013. Model uncertainty and exchange rate forecasting. J. Financ. Quant. Anal. 52 (1), 341–363.
Kuan, C.M., Liu, T., 1995. Forecasting exchange rates using feedforward and recurrent neural networks. J. Appl. Econom. 10 (4), 347–364.
Leung, M.T., Chen, A.S., Daouk, H., 2000. Forecasting exchange rates using general regression neural networks. Comput. Oper. Res. 27 (11–12), 1093–1110.
Lin, C., Chiu, S., Lin, T., 2012. Empirical mode decomposition-based least squares support vector regression for foreign exchange rate forecasting. Econ. Modell. 29 (6), 2583–2590.
Ludwig, O., Nunes, U., Araujo, R., 2014. Eigenvalue decay: a new method for neural network regularization. Neurocomputing 124, 33–42.
McCrae, M., Lin, Y.X., Pavlik, D., Gulati, C.M., 2002. Can cointegration-based forecasting outperform univariate models? An application to Asian exchange rates. J. Forecast. 21 (5), 355–380.
Moosa, I.A., Vaz, J.J., 2016. Cointegration, error correction and exchange rate forecasting. J. Int. Financ. Mark. Inst. Money 44, 21–34.
Mostafa, M.M., El-Masry, A.A., 2016. Oil price forecasting using gene expression programming and artificial neural networks. Econ. Modell. 54, 40–53.
Nag, A.K., Mitra, A., 2002. Forecasting daily foreign exchange rates using genetically optimized neural networks. J. Forecast. 21 (7), 501–511.
Niu, M.F., Gan, K., Sun, S.L., Li, F.Y., 2017. Application of decomposition-ensemble learning paradigm with phase space reconstruction for day-ahead $PM_{2.5}$ concentration forecasting. J. Environ. Manag. 196, 110–118.
Niu, M.F., Wang, Y.F., Sun, S.L., Li, Y.W., 2016. A novel hybrid decomposition-and-ensemble model based on CEEMD and GWO for short-term $PM_{2.5}$ concentration forecasting. Atmos. Environ. 134, 168–180.
Özkan, F., 2013. Comparing the forecasting performance of neural network and purchasing power parity: the case of Turkey. Econ. Modell. 31, 752–758.
Pesaran, M.H., Timmermann, A., 1992. A simple nonparametric test of predictive performance. J. Bus. Econ. Stat. 10 (4), 461–465.
Plakandaras, V., Papadimitriou, T., Gogas, P., 2015. Forecasting daily and monthly exchange rates with machine learning techniques. J. Forecast. 34 (7), 560–573.
Ribeiro, P.J., 2017. Selecting exchange rate fundamentals by bootstrap. Int. J. Forecast. 33 (4), 894–914.
Sermpinis, G., Dunis, C., Laws, J., Stasinakis, C., 2012. Forecasting and trading the EUR/USD exchange rate with stochastic neural network combination and time-varying leverage. Decis. Support Syst. 54 (1), 316–329.
Sermpinis, G., Stasinakis, C., Theofilatos, K., Karathanasopoulos, A., 2015. Modeling, forecasting and trading the EUR exchange rates with hybrid rolling genetic algorithms-Support vector regression forecast combinations. Eur. J. Oper. Res. 247 (3), 831–846.
Sermpinis, G., Theofilatos, K., Karathanasopoulos, A., Georgopoulos, E.F., Dunis, C., 2013. Forecasting foreign exchange rates with adaptive neural networks using radial-basis functions and particle swarm optimization. Eur. J. Oper. Res. 225 (3), 528–540.
Shen, F., Chao, J., Zhao, J., 2015. Forecasting exchange rate using deep belief networks and conjugate gradient method. Neurocomputing 167, 243–253.
Sun, S.L., Qiao, H., Wei, Y., Wang, S., 2017. A new dynamic integrated approach for wind speed forecasting. Appl. Energy 197, 151–162.
Sun, S.L., Wang, S., Wei, Y.J., Zhang, G.W., 2018. A clustering-based nonlinear ensemble approach for exchange rates forecasting. IEEE Trans. Syst. Man Cybern. Syst. https://doi.org/10.1109/TSMC.2018.2799869.
Tang, L., Yu, L., Wang, S., Li, J., Wang, S., 2012. A novel hybrid ensemble learning paradigm for nuclear energy consumption forecasting. Appl. Energy 93, 432–443.
Vapnik, V., 1995. The Nature of Statistic Learning Theory. Springer-Verlag, New York.
Wei, L.Y., 2013. A hybrid model based on ANFIS and adaptive expectation genetic algorithm to forecast TAIEX. Econ. Modell. 33, 893–899.
West, K.D., Cho, D., 1995. The predictive ability of several models of exchange rate volatility. J. Econom. 69 (2), 367–391.
Wright, J.H., 2008. Bayesian model averaging and exchange rate forecasts. J. Econom. 146 (2), 329–341.
Xiong, T., Li, C., Bao, Y., 2017. Interval-valued time series forecasting using a novel hybrid HoltI and MSVR model. Econ. Modell. 60, 11–23.
Yu, L., Wang, S., Lai, K.K., 2005. A novel nonlinear ensemble forecasting model incorporating GLAR and ANN for foreign exchange rates. Comput. Oper. Res. 32 (10), 2523–2541.
Yu, L., Wang, S., Lai, K.K., 2008. Forecasting crude oil price with an EMD-based neural network ensemble learning paradigm. Energy Econ. 30 (5), 2623–2635.
Yu, L., Wang, S., Lai, K.K., 2009. A neural-network-based nonlinear metamodeling approach to financial time series forecasting. Appl. Soft Comput. 9 (2), 563–574.
Yu, L., Wang, Z., Tang, L., 2015. A decomposition-ensemble model with data-characteristic-driven reconstruction for crude oil price forecasting. Appl. Energy 156, 251–267.
Zhang, G.P., 2003. Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing 50 (1), 159–175.
Zhang, G.P., Berardi, V.L., 2001. Time series forecasting with neural network ensembles: an application for exchange rate prediction. J. Oper. Res. Soc. 2 (6), 52–664.
Zhang, G.P., Hu, M.Y., 1998. Neural network forecasting of the British pound/US dollar exchange rate. Omega 26 (4), 495–506.
Zorzi, M.C., Kolasa, M., Rubaszek, M., 2017. Exchange rate forecasting with DSGE models. J. Int. Econ. 107, 127–146.
Zhang, X., Yu, L., Wang, S., Lai, K.K., 2009. Estimating the impact of extreme events on crude oil price: an EMD-based event analysis method. Energy Econ. 31 (5), 768–778.