Economic Modelling 29 (2012) 2583–2590

Contents lists available at SciVerse ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/ecmod

Empirical mode decomposition–based least squares support vector regression for foreign exchange rate forecasting

Chiun-Sin Lin [a], Sheng-Hsiung Chiu [b], Tzu-Yu Lin [b,*]

[a] Department of Business and Entrepreneurial Management, Kainan University, No.1 Kainan Road, Luzhu Shiang, Taoyuan 33857, Taiwan
[b] Department of Management Science, National Chiao Tung University, No. 1001, Ta-Hsueh Road, Hsinchu City 30010, Taiwan

ARTICLE INFO

Article history:
Accepted 11 July 2012

Keywords:
Empirical mode decomposition
Least-squares support vector regression
Foreign exchange rate forecasting
Intrinsic mode function

ABSTRACT

To address the nonlinear and non-stationary characteristics of financial time series such as foreign exchange rates, this study proposes a hybrid forecasting model using empirical mode decomposition (EMD) and least squares support vector regression (LSSVR) for foreign exchange rate forecasting. EMD is used to decompose the dynamics of foreign exchange rate into several intrinsic mode function (IMF) components and one residual component. LSSVR is constructed to forecast these IMFs and residual value individually, and then all these forecasted values are aggregated to produce the final forecasted value for foreign exchange rates. Empirical results show that the proposed EMD-LSSVR model outperforms the EMD-ARIMA (autoregressive integrated moving average) as well as the LSSVR and ARIMA models without time series decomposition.

1. Introduction

Financial time series forecasting has come to play an important role in the world economy as a result of its ability to forecast economic benefits and influence countries' economic development; it has attracted increasing attention from academic researchers and business practitioners for its theoretical possibilities and practical applications (Hadavandi et al., 2010; Lu et al., 2009). Since the breakdown of financial market boundaries in order to enhance the efficiency of capital funding, for example, the Bretton Woods system of monetary management was officially ended in the 1973; currencies traded internationally has become crucial economic indices for international trade, financial markets, the alignment of economic policy by governments, and corporate financial decision-making. However, it is widely known that financial time series forecasting has shortcomings, including its inherent nonlinearity and non-stationarity (Huang et al., 2010; Lu et al., 2009). Therefore, financial time series forecasting is one of the most challenging tasks in the financial markets.

For modeling financial time series, autoregressive integrated moving average (ARIMA) models have been popular and are widely chosen for academic research observing the behavior of foreign exchanges and stock markets, because of their statistical properties and forecasting performance (Khashei et al., 2009). However, some problems arise when forecasting financial time series with ARIMA models, as follows. First is the characteristic linear limitation of ARIMA models, in contrast to real-word financial time series, which are often nonlinear (Khashei et al., 2009; Zhang, 2001; Zhang et al., 1998) and are rarely pure linear combinations. Second is the robustness limitation of ARIMA models—the ARIMA model selection procedure depends greatly on the competence and experience of the researchers to yield desired results. Unfortunately, choice among competing models can be arbitrated by similar estimated correlation patterns and may frequently reach inappropriate forecasting results.

With the recent development of machine-learning algorithms, several methods have been utilized that work more effectively than the traditional linear model in time series forecasting problems. For example, the support vector machine (SVM) is a novel machine-learning approach. SVM's generalization capability in obtaining a unique solution (Lu et al., 2009) and structural risk minimization principle (SRM) in achieving high performance (Duan and Stanley, 2011) have drawn attention to SVM's research applications. Support vector regression (SVR) is the regression model of SVM (Vapnik, 2000). It has been applied to investigate the forecasting ability of financial time series. Lu et al. (2009) used SVR to construct a stock price forecasting model, and Huang et al. (2010) and Ni and Yin (2009) both implemented SVR in exchange rate forecasting models. However, the training phrase of SVR is a time-consuming process when there is a lot of data to deal with. Therefore, least squares support vector regression (LSSVR), proposed by Suykens and Vandewalle (1999), has been applied in much literature as an alternative (He et al., 2010; Khemchandani et al., 2009); it is a simplified version of traditional SVR that alters inequality constraints into equal conditions and employs a squared loss function, which is a differential setting relative to traditional SVR (Wang et al., 2011), to achieve higher calculation speed and efficiency while retaining the advantage of the structural risk minimization principle.

* Corresponding author. Tel.: +886 921865025.
E-mail address: blackmallows@gmail.com (T.-Y. Lin).

0264-9993/$ – see front matter © 2012 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.econmod.2012.07.018

When we model financial time series using LSSVR or ARIMA, we must remember that these financial time series are inherently nonlinear and non-stationary. If we ignore this problem, it will result in worse forecasting. The property of financial time series and the divide and conquer principle (Yu et al., 2008) are important in constructing a financial time series forecasting model. Therefore, hybrid models are widely used to solve the limitations in financial time series forecasting. Empirical mode decomposition (EMD) is suitable for financial time series in terms of finding fluctuation tendency, which simplifies the forecasting task into several simple forecasting subtasks. EMD as a time–frequency resolution approach offers a new way by which the -stationary and nonlinear behavior of time series can be decomposed into a series of valuable independent time resolutions (Tang et al., 2012). It also can reveal the hidden patterns and trends of time series, which can effectively assist in designing forecasting models for various applications (An et al., 2012; Guo et al., 2012). Guo et al. (2012), for example, decomposed wind-speed series using EMD and then forecasted them using a feed-forward neural network, whereas Chen et al. (2012) proposed an EMD approach combined with an artificial neural network for tourism-demand forecasting.

In this paper, EMD and LSSVR are used to present a financial time series forecasting model for foreign exchange rate, in which consideration of the decomposed financial time series structure will increase the accuracy and practicability of the proposed model in terms of overcoming the nonlinearity and non-stationarity limitations to the linear statistical model. The proposed approach is compared with the combination of EMD and ARIMA as well as with the existing LSSVR and ARIMA models, and it is shown that the proposed model can yield more accurate results. Three financial time series are used as illustrative examples, as follows: USD/NTD exchange rate, JPY/NTD exchange rate, and RMB/NTD exchange rate.

2. Methodology

2.1. Empirical mode decomposition

Empirical mode decomposition (EMD) is a nonlinear signal-transformation method developed by Huang et al. (1998, 1999). It is used to decompose a nonlinear and non-stationary time series into a sum of intrinsic mode function (IMF) components with individual intrinsic time scale properties. According to Huang et al. (1998), each IMF must satisfy the following two conditions. First, the number of extreme values and zero-crossings either are equal or differ at the most by one; and second, the mean value of the envelope constructed by the local maxima and minima is zero at any point. The detail-decomposition process of EMD is presented by Huang et al. (1998). Suppose that a data time series can be decomposed according to the following procedure.

(1) Identify all the local maxima and minima of $x(t)$.
(2) Obtain the upper envelope $x_u(t)$ and the lower envelope $x_l(t)$ of the $x(t)$.
(3) Use the upper envelope $x_u(t)$ and the lower envelope $x_l(t)$ to compute the first mean time series $m_1(t)$, that is, $m_1(t)=[x_u(t)+x_l(t)]/2$.
(4) Evaluate the difference between the original time series $x(t)$ and the mean time series and get the first IMF $h_1(t)$, that is, $h_1(t)=x(t)-m_1(t)$. Moreover, we see whether $h_1(t)$ satisfies the two conditions of an IMF property. If they are not satisfied, we repeat steps 1–3 of the decomposition procedure to eventually find the first IMF.
(5) After we obtain the first IMF, a repeat of the above steps is necessary to find the second IMF, until we reach the final time series $r(t)$ as a residue component that becomes a monotonic function, which is suggested for stopping the decomposition procedure (Huang et al., 1999).

The original time series $x(t)$ can be reconstructed by summing up all the IMF components and one residue component as Eq. (1), as follows.

$$x(t)=\sum_{i=1}^{n} h_i(t)+r(t). \tag{1}$$

2.2. Least squares support vector regression

The support vector machine (SVM) developed by Vapnik (1995, 2000) is based on the SRM principle. It aims to minimize the upper bound of the generalization error, instead of the empirical error as in other neural-network methods such as back-propagation networks (BPN). SVM explores not only the problem of classification but also the regression application of forecasting. Vapnik et al. (1997) proposed support vector regression (SVR) as an SVM regression estimation model, introducing the concept of the ε-loss function.

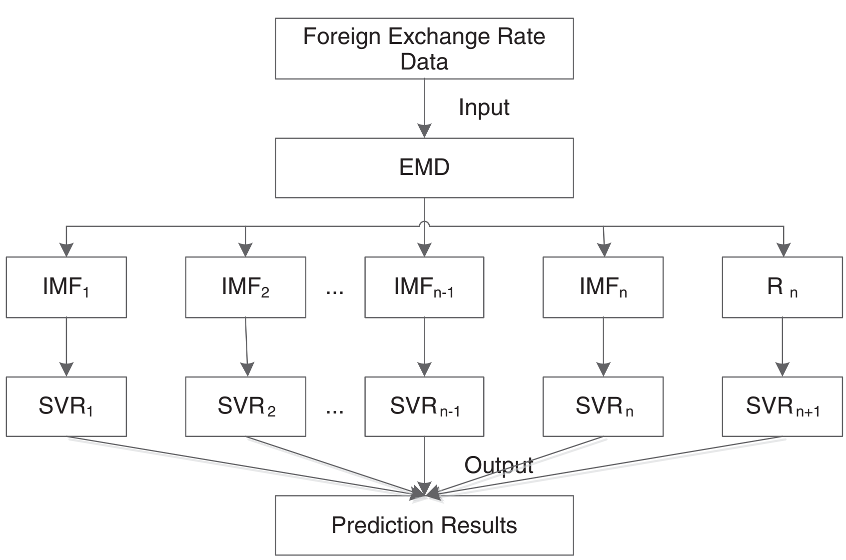

Fig. 1. The proposed EMD-LSSVR forecasting model for foreign exchange rate.

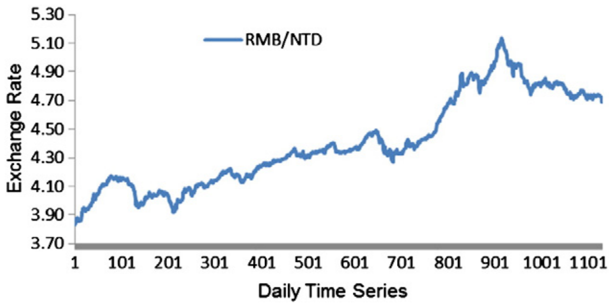

Fig. 2. The daily USD/NTD exchange rate form July 2005 to December 2009.

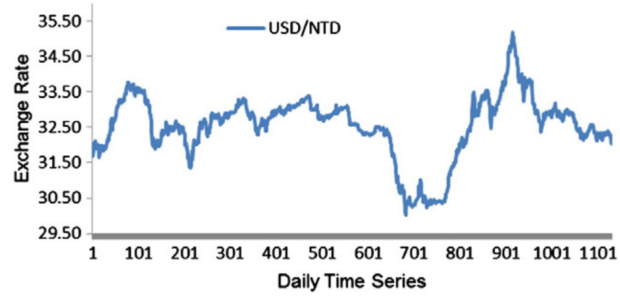

Fig. 4. The daily RMB/NTD exchange rate form July 2005 to December 2009.

SVR performs by nonlinearly mapping the input space into a high-dimensional feature space, and then runs the linear regression in the output space. This allows us to formulate the nonlinear relationship between input data and output data. The formulation of SVR basically is represented the following linear estimation function:

$$f(x) = \omega \cdot \phi(x_i) + b, \tag{2}$$

where ω denotes the weight vector, b is the bias, $\phi(x_i)$ represents a mapping function that aims to map the input vectors into a high-dimensional feature space, and $\omega \cdot \phi(x_i)$ describes the dot production in the feature space.

In SVR, the problem of nonlinear regression in the low-dimension input space is transformed into a linear regression problem in a high-dimension feature space. That is, the original optimization problem involving a nonlinear regression is recast as a search for the flattest function in the feature space, not in the input space. However, LSSVR is the least squares version of SVR, and finds the solution by solving a set of linear equations instead of a quadratic programming problem (Iplikci, 2006). In LLSVR, the regression problem can be applied to the following optimization problem:

$$\min \frac{1}{2}\|\omega\|^2 + \frac{1}{2} C \sum_{i=1}^{l} e_i^2 \quad , \qquad s.t. y_i = \omega \cdot \phi(x_i) + b + e_i (i = 1, \ldots, l) \tag{3}$$

where e_i represents the error from the training set and C is the penalty parameter to be used to limit the minimization of estimation error and function smoothness.

In order to derive the optimization problem of Eq. (3), the Lagrange function is formulated for Eq. (3) to find out the solutions to ω and e; this can be written as follows.

$$L(w, b, e; \alpha) = \frac{1}{2}\|\omega\|^2 + \frac{1}{2} C \sum_{i=1}^{l} e_i^2 - \sum_{i=1}^{l} \alpha_i \{\omega \cdot \phi(x_i) + b + e_i - y_i\}, \tag{4}$$

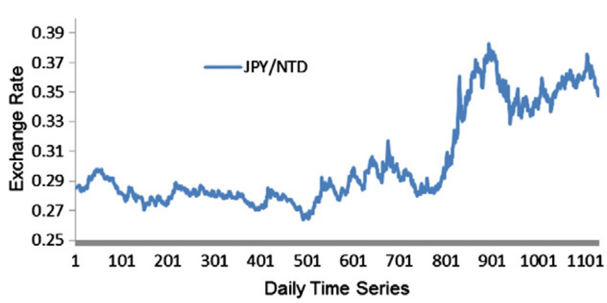

Fig. 3. The daily JPY/NTD exchange rate form July 2005 to December 2009.

where $\alpha_i = (\alpha_1, \ldots, \alpha_l)$ are Lagrange multipliers, which can be expressed as either positive or negative. The first-order conditions for optimality are as follows.

$$\frac{\partial L}{\partial \omega} = \omega - \sum_{i=1}^{l} \alpha_i \phi(x_i) = 0 \tag{5}$$

$$\frac{\partial L}{\partial b} = \sum_{i=1}^{l} \alpha_i = 0 \tag{6}$$

Table 1
Descriptive statistics of the exchange rare data.

Currencies	Numbers	Mean	Standard deviation	Max	Min
USD/NTD					
All sample	1130	32.537	0.895	35.174	30.010
Training	904	32.424	0.894	34.050	30.010
Testing	226	32.987	0.745	35.174	32.030
JPY/NTD					
All sample	1130	0.303	0.032	0.383	0.264
Training	904	0.291	0.023	0.383	0.264
Testing	226	0.351	0.010	0.375	0.329
RMB/NTD					
All sample	1130	4.403	0.313	5.138	3.829
Training	904	4.297	0.251	4.294	3.829
Testing	226	4.829	0.107	5.138	4.692

Table 2
Performance and their definition.

Metrics	Calculation
MAPE	$\text{MAPE} = \frac{1}{n} \times \sum_{i=1}^{n} \left\| \frac{T_i - A_i}{T_i} \right\| \times 100\%$
RMSE	$\text{RMSE} = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (T_i - A_i)^2}$
MAD	$\text{MAD} = \frac{1}{n} \times \sum_{i=1}^{n} \|T_i - A_i\|$
DS	$\text{DS} = \frac{100}{n} \sum_{u=1}^{n} d_i, \quad \text{where } d_i = \begin{Bmatrix} 1 (T_i - T_{t-1})(A_i - A_{t-1}) \geq 0 \\ 0 \quad \text{otherwise} \end{Bmatrix}$
CP	$\text{CP} = \frac{100}{n_1} \sum_{u=1}^{n} d_i, \quad \text{where } d_i = \begin{cases} 1 (A_I - A_{t-1}) > 0 \text{ and } (T_i - T_{t-1})(A_i - A_{t-1}) \geq 0 \\ 0 \quad \text{otherwise} \end{cases}$
CD	$\text{CD} = \frac{100}{n_2} \sum_{u=1}^{n} d_i, \quad \text{where } d_i = \begin{cases} 1 (A_I - A_{t-1}) < 0 \text{ and } (T_i - T_{t-1})(A_i - A_{t-1}) \geq 0 \\ 0 \quad \text{otherwise} \end{cases}$

Note that A and T represent the actual and forecasted value, respectively. n is total number of data points, n_1 is number of data points belong to up trend and n_2 is number of data points belong to down trend.

$$\frac{\partial L}{\partial e_i} = C \cdot e_i - \alpha_i = 0 \quad (7)$$

$$\frac{\partial L}{\partial \alpha_i} = \omega \cdot \phi(x_i) + b + e_i - y_i = 0. \quad (8)$$

By solving the above linear system, the forecasting formulation of LSSVR can be represented in the following equation:

$$f(x) = \sum_{i=1}^{l} \alpha_i K\left(x_i, x_j\right) + b, \quad (9)$$

where $K(x_i,x_j)$ is called the "kernel function" and must satisfy Mercer's theorem (Vapnik, 1995). The value of the kernel equals the inner product of two vectors, x_i and x_j, in the feature space $\phi(x_i)$ and $\phi(x_j)$; that is, $K(x_i,x_j) = \phi(x_i) \cdot \phi(x_j)$.

The most widely used kernel function is the Gaussian radial basis function (RBF), defined as $K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right)$, where σ denotes the width of the RBF. Moreover, the RBF kernel is not only easier to implement than alternatives, but also capable of nonlinearly mapping the training data into an infinite-dimensional space; thus, it deals suitably with nonlinear relationship problems. Thus, the Gaussian RBF kernel function is used in this work. LSSVR parameter selection is

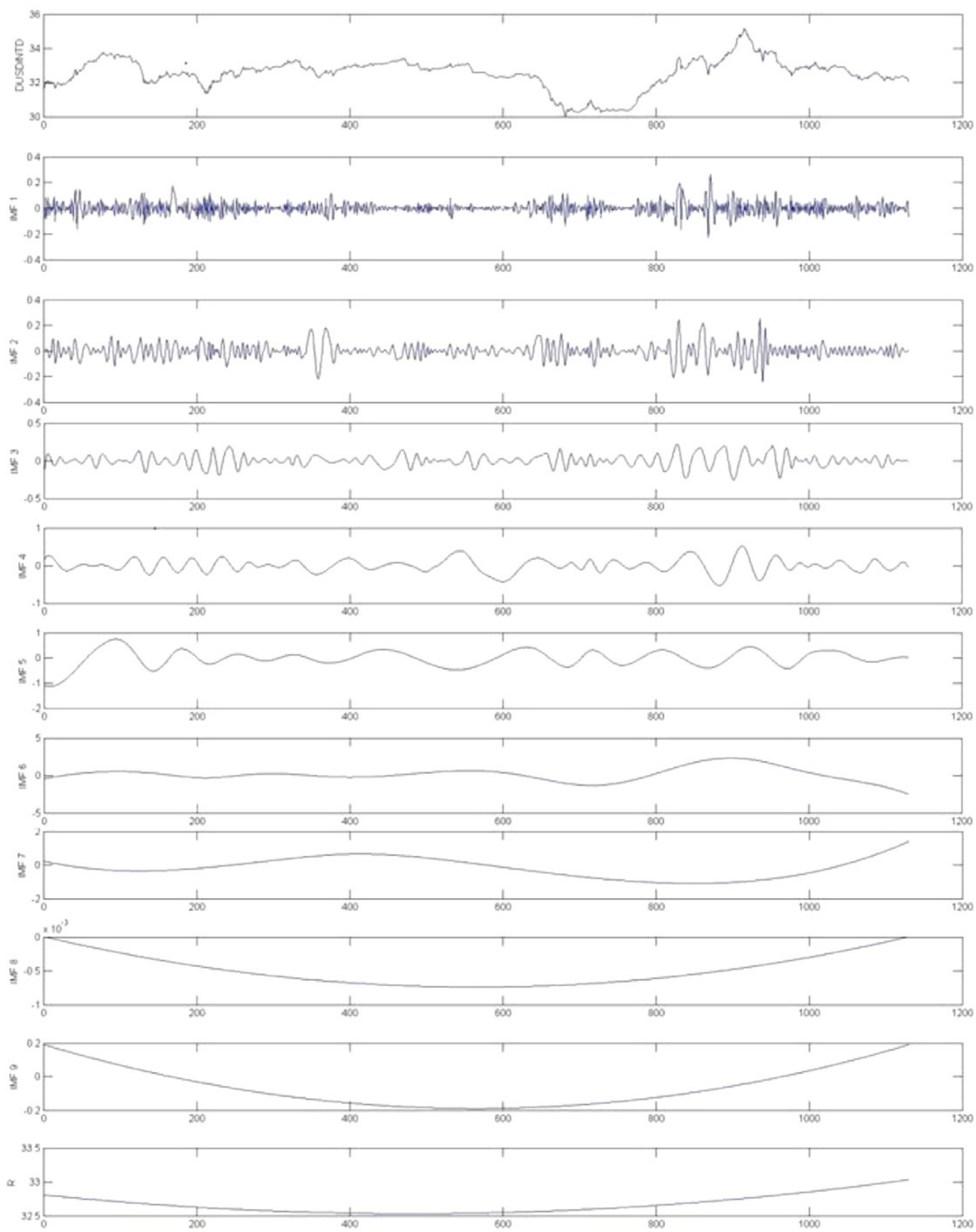

Fig. 5. The decomposition results for USD/NTD from EMD approach.

most important, so that we can see that the established LLSVR model with Gaussian RBF kernel function goes well, because these parameters can significantly affect generalized performance. Grid search (He et al., 2010), one of the most useful methods for parameter optimization, is applied to find the optimal parameters, C and σ, in LSSVR model construction.

3. Proposed EMD-LSSVR model

Many studies have used least squares support vector regression in practice problems (Khemchandani et al., 2009; Lin et al., in press). In financial time series forecasting, however, the major problems are inherent nonlinearity and non-stationary properties affecting the robustness of the LSSVR model significantly. For this reason, the proposed EMD-LSSVR model is employed according to the principle of decomposition and ensemble (He et al., 2010; Wang et al., 2011). The procedure of the proposed EMD-LSSVR structure is shown in Fig. 1 and generally consists of the following three steps: (1) data decomposition, (2) forecasting-model construction, and (3) data reconstruction and validation.

(1) Suppose there is a foreign exchange rate time series $x(t)$ that also can be decomposed into n IMF components, $h_i(t)$, $i=1, 2,\ldots,n$, and one residue component, $r(t)$, through the EMD approach, as in Eq. (1).
(2) After the data decomposition, each obtained IMF component and residual component is further input to the LSSVR forecasting

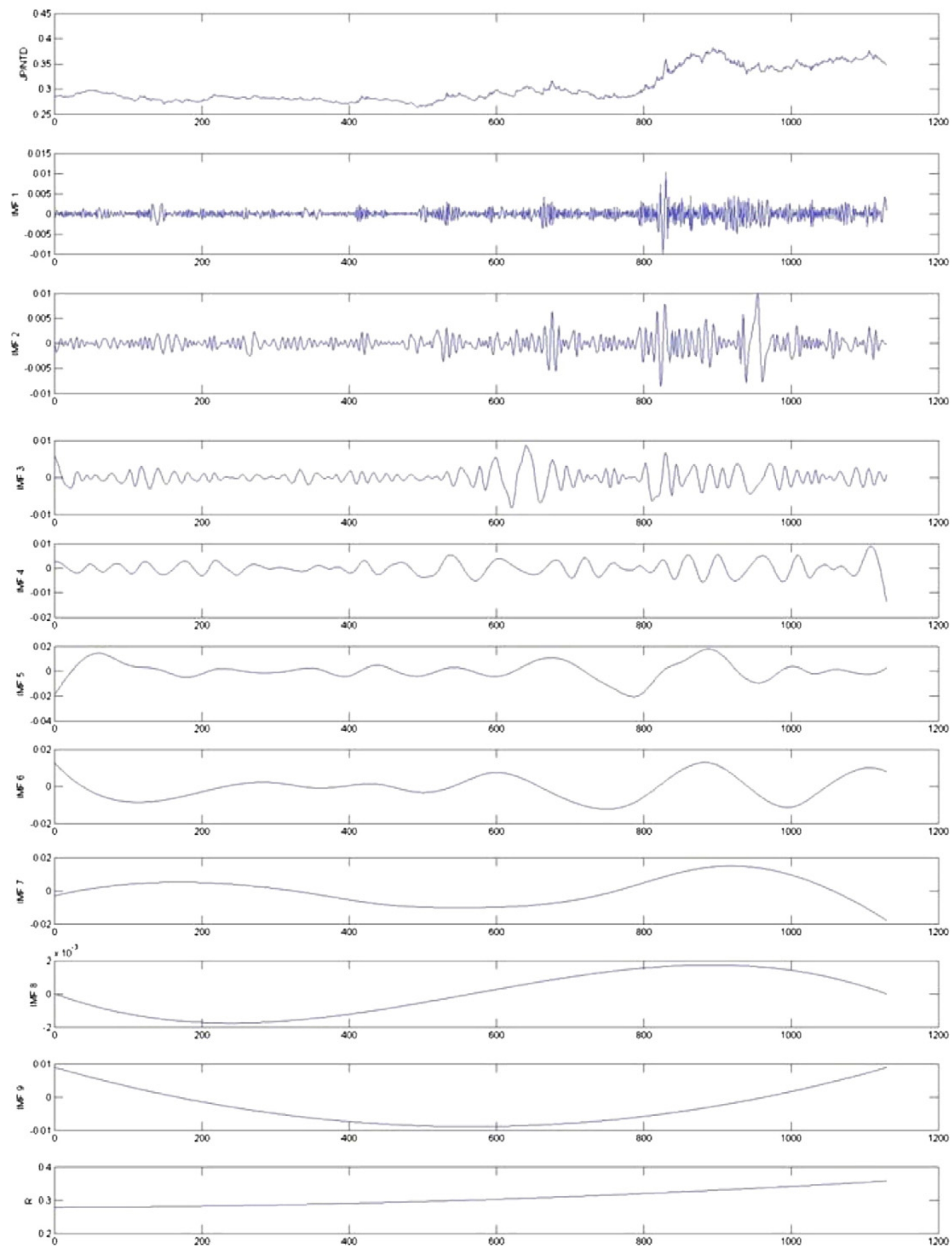

Fig. 6. The decomposition results for JPY/NTD from EMD approach.

model; consequently, the corresponding forecasted values for all IMF and residual components are acquired from the forecasting tool.

(3) The forecasted value of each IMF and residual component in the previous stage can be reconstructed as a sum of superposition of all components, which can be used as the final forecasting result, and then compared with the original time series according to several criteria for measuring the performance capability of this proposed model.

4. Experimental results

4.1. Exchange rate dataset

To evaluate the performance of the proposed forecasting models using EMD with LSSVR methodologies, this study uses daily USD/NTD, JPY/NTD, and RMB/NTD exchange rates obtained from the Central Bank of Taiwan and Yahoo Finance. The whole daily data of exchange rates from July 1, 2005 to December 31, 2009 are used, for a total of

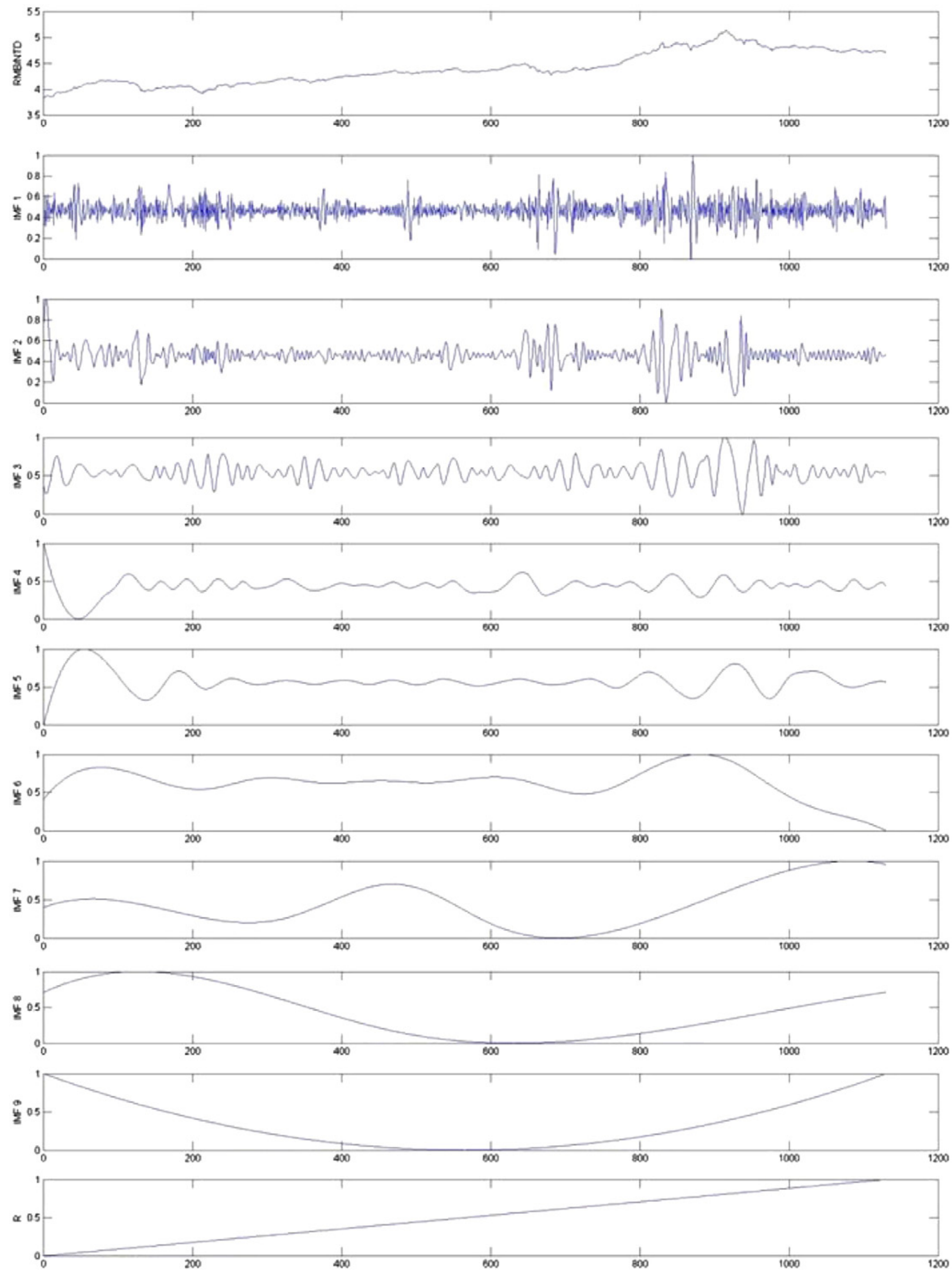

Fig. 7. The decomposition results for RMB/NTD from EMD approach.

1130 data points, as illustrated in Figs. 2–4 for each of the three rates respectively. These datasets are also divided into training group and testing group in separate foreign exchange rate categories. The first 904 data points (80% of the total dataset) are used as the training group and the remaining 226 data points are used as the testing group. Table 1 shows some basic summary statistics for total, training, and testing data within the three foreign exchange rate datasets.

4.2. Performance criteria

Following Lu et al. (2009) and Tay and Cao (2001), the following performance measures are used and evaluated respectively: applied mean absolute percentage error (MAPE), root-mean-square error (RMSE), mean absolute difference (MAD), directional symmetry (DS), correct uptrend (CP), and correct downtrend (CD) for consideration. The definition of these criteria can be summarized in Table 2. MAPE, RMSE, and MAD are measures of the deviation between the actual and forecasted value. They can be used to evaluate forecasting error. The smaller the values of the criteria, the closer the forecasted value to the actual value. DS provides the correctness of the forecasted direction of the exchange rate in terms of percentage, while CP and CD provide the correctness of the forecasted up trend and down trends of exchange rate, also in terms of percentage. DS, CP, and CD can be utilized to provide forecasting accuracy.

4.3. Forecasting results

In this section, the forecasting results of the EMD-LSSVR model are compared to those of other linear and nonlinear models. First is another hybrid forecasting model, one that integrates EMD with ARIMA. EMD is applied to decompose the foreign exchange rate time series, and gathered components that have a monotonic function, enhancing the forecasting ability of LSSVR and ARIMA. The others are the single LSSVR and ARIMA models without algorithms or treatments for forecasting. That is, the single LSSVR and ARIMA model were directly applied to forecast future exchange rates. The purpose of doing so is to explore the problem of financial time series forecasting based on linear and nonlinear models, whether we can preprocess forecasting variables using the EMD approach or not, thus helping to further managerial applications.

The modeling steps of the proposed EMD-LSSVR are shown in Section 3. Using the EMD approach in the data decomposition, the three foreign exchange rate time series can be decomposed into nine independent IMFs and one residue component, respectively, as illustrated in Figs. 5–7. These decomposition results may enhance the model's forecasting ability in terms of the divide and conquer concept (Yu et al., 2008). Then, the decomposed forecasting variables, the independent IMFs, and residual components from the previous step, are used in LSSVR model construction. Parameter selection is essential for LSSVR model construction; we employ the Gaussian RBF as the kernel function of LSSVR. The parameter combination (C and σ) was selected by grid search, as suggested in He et al. (2010) and Van Gestel et al. (2004). The optimal values of C and σ for each EMD-LSSVR forecasting model are presented in Table 3. At the reconstruction step, we combine all forecasted values from the individual EMD-LSSVR models in order to compare them with the actual foreign exchange rate date, so as to validate the forecasting ability of the EMD-LSSVR model.

The same EMD-based methodology steps are also fed into ARIMA in order to build the hybrid linear foreign exchange rate forecasting model, namely, the EMD-ARIMA model, the results of which are compared with those of the EMD-LSSVR model. As well, the pure LSSVR and ARIMA models are applied for comparison. The optimal parameter combination selected for the single LSSVR model is listed in Table 4, and the performance evaluation of each forecasting model is based on the several performance criteria from Section 4.2, as listed in Table 2. The performance measurements of the selected forecasting models are given in Table 5.

Table 3
The parameter selection of EMD-LSSVR forecasting model.

Kernel	USD/NTD			JPY/NTD			RMB/NTD		
RBF	Set	C	σ	Set	C	σ	Set	C	σ
	1	0.5	0.00390625	1	8	0.00390625	1	0.5	0.015625
	2	64	1	2	1	0.00390625	2	0.5	0.00390625
	3	64	1	3	64	0.5	3	1	0.0078125
	4	16	0.5	4	64	0.5	4	64	1
	5	64	1	5	64	1	5	32	1
	6	64	1	6	64	1	6	64	1
	7	64	1	7	64	1	7	32	1
	8	64	1	8	64	1	8	64	1
	9	64	1	9	64	0.015625	9	32	0.25
	10	64	1	10	64	1	10	64	1

Table 4
The parameter selection of single LSSVR forecasting model.

Kernel	USD/NTD		JPY/NTD		RMB/NTD	
RBF	C	σ	C	σ	C	σ
	64	0.25	64	0.125	64	0.0312

4.4. Comparison of forecasting results

In order to verify the forecasting capability of the proposed EMD-LSSVR model, the EMD-ARIMA, LSSVR and ARIMA models are employed for comparison, using three foreign exchange rate data sets: (1) the USD/NTD exchange rate data set, (2) the JPY/NTD exchange rate data set, and (3) the RMB/NTD exchange rate data set. MAPE, RMSE, MAD, DS, CP and CD, which are computed from the equations mentioned in Table 2, are used as performance indicators to further survey the forecasting performance of the proposed EMD-LSSVE model as compared to other linear and nonlinear models.

Take the USD/NTD exchange rate as an example-the forecasting results using EMD-LSSVR, EMD-ARIMA, LSSVR, and ARIMA are computed and listed in Table 5, where can be seen that the MAPE, RMSE, and MAD of the EMD-LSSVR model are, respectively, 0.21%, 0.0188, and 0.0135. These values are the smallest of all the forecasting models, that the deviation between actual and forecasted values in the EMD-LSSVR model is the smallest. Moreover, EMD-LSSVR also has higher

Table 5
The exchange rate forecasting results using EMD-LSSVR, EMD-ARIMA, LSSVR and ARIMA models.

Models	Indicators					
	MAPE (%)	REMSE	MAD	DS (%)	CP (%)	CD (%)
USD/NTD						
EMD-LSSVR	0.48	0.0109	0.0081	86.37	87.88	86.28
EMD-ARIMA	1.21	0.0173	0.0159	80.78	74.46	84.19
LSSVR	1.06	0.0262	0.0231	83.54	82.12	83.42
ARIMA	11.06	0.1039	0.1020	73.53	74.77	73.09
JPY/NTD						
EMD-LSSVR	0.57	0.0026	0.0020	86.37	87.63	82.74
EMD-ARIMA	2.29	0.0183	0.0150	83.89	82.54	86.17
LSSVR	2.94	0.0267	0.0212	81.77	78.55	82.22
ARIMA	7.19	0.0302	0.0400	73.67	76.17	70.75
RMB/NTD						
EMD-LSSVR	0.48	0.0109	0.0081	86.37	87.88	86.28
EMD-ARIMA	1.21	0.0173	0.0159	80.78	74.46	84.19
LSSVR	1.06	0.0262	0.0231	83.54	82.12	83.42
ARIMA	11.06	0.1039	0.1020	73.53	74.77	73.09

Table 6
Percentage improvement of forecasting performance of the proposed EMD-LSSVR model in comparison with other forecasting models.

Models	Indicators					
	MAPE	REMSE	MAD	DS	CP	CD
USD/NTD						
EMD-ARIMA	82.79	62.85	66.67	8.02	15.71	3.56
LSSVR	91.03	79.76	80.93	5.01	4.01	7.00
ARIMA	98.23	81.01	81.38	17.51	13.06	26.91
JPY/NTD						
EMD-ARIMA	75.11	85.79	86.67	2.96	6.17	3.98
LSSVR	80.61	90.26	90.57	5.63	11.56	0.63
ARIMA	92.07	91.39	95.00	17.24	15.05	16.95
RMB/NTD						
EMD-ARIMA	60.33	36.99	49.06	6.92	18.02	2.48
LSSVR	54.72	58.40	64.94	3.39	7.01	3.43
ARIMA	95.66	89.51	92.06	14.46	17.53	18.05

DS, CP, and CD ratios, 87.26%, 85.88%, and 89.38%, respectively. DS, CP, and CD provide a good measure of forecasting consistency of moving exchange rate trends. In sum, it can be concluded that EMD-LSSVR provides better forecasting accuracy and direction criteria for USD/NTD exchange rate than EMD-ARMA, LSSVR, or ARIMA. In addition, the results of EMD-LSSVR are consistent with the principle of decomposition and ensemble (He et al., 2011; Wang et al., 2010). Time series decomposition may enhance forecasting ability. For example, in terms of DS indicators from the USD/NTD exchange rate forecasting, as shown in Table 6, relative to the comparison models, the improvement percentages of the proposed model are 8.02%, 5.01% and 17.51%, respectively.

The forecasting results and performance comparisons of the four forecasting models for JPY/NTD and RMB/NTD are also reported in Tables 5 and 6. In addition, we see that the decomposition of time series in EMD can enhance the forecasting ability of nonlinear and linear models.

5. Conclusions

There has been increasing attention given to finding an effective model to address the problem of financial time series forecasting in terms of nonlinear and non-stationary characteristics. In this paper, an EMD-based LSSVR forecasting model is proposed. EMD is used to detect the moving trend of financial time series data and improve the forecasting success of LSSVR. Through empirical comparison of several models of foreign exchange rate forecasting, the proposed EMD-LSSVR model outperforms EMD-ARIMA, LSSVR and ARIMA on several criteria. Thus, it can be concluded that the proposed EMD-LSSVR model may be an effective tool for financial time series forecasting.

References

An, X., Jiang, D., Zhao, M., Liu, C., 2012. Short-time prediction of wind power using EMD and chaotic theory. Communications in Nonlinear Science and Numerical Simulation 17 (2), 1036–1042.

Chen, C.F., Lai, M.C., Yeh, C.C., 2012. Forecasting tourism demand based on empirical mode decomposition and neural network. Knowledge-Based System 26, 281–287.

Duan, W.Q., Stanley, H.E., 2011. Cross-correlation and the predictability of financial return series. Physica A 390 (2), 290–296.

Guo, Z., Zhao, W., Lu, H., Wang, J., 2012. Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model. Renewable Energy 37 (1), 241–249.

Hadavandi, E., Shavandi, H., Ghanbari, A., 2010. Integration of genetic fuzzy systems and artificial neural networks for stock price forecasting. Knowledge-Based System 23 (8), 800–808.

He, K., Lai, K.K., Yen, J., 2010. A hybrid slantlet denoising least squares support vector regression model for exchange rate prediction. Procedia Computer Science 1 (1), 2397–2405.

Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.C., Tung, C.C., Liu, H.H., 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences 454, 903–995.

Huang, N.E., Shen, Z., Long, S.R., 1999. A new view of nonlinear water waves: the Hilbert spectrum. Annual Review of Fluid Mechanics 31, 417–457.

Huang, S.C., Chuang, P.J., Wu, C.F., 2010. Chaos-based support vector regressions for exchange rate forecasting. Expert Systems with Applications 37 (12), 8590–8598.

Iplikci, S., 2006. Dynamic reconstruction of chaotic systems from inter-spike intervals using least square support vector machine. Physica D 216, 282–293.

Khashei, M., Bijari, M., Ali Raissi Ardali, G., 2009. Improvement of auto-regressive integrated moving average models using fuzzy logic and artificial neural networks (ANNs). Neurocomputing 72 (4–6), 956–967.

Khemchandani, R., Jayadeva, Chandra, S., 2009. Regularized least squares fuzzy support vector regression for financial time series forecasting. Expert Systems with Applications 36 (1), 132–138.

Lin, K.P., Pai, P.F., Lu, Y.M., Chang, P.T., in press. Revenue forecasting using a least-squares support vector regression model in a fuzzy environment. Information Sciences. http://dx.doi.org/10.1016/j.ins.2011.09.003

Lu, C.J., Lee, T.S., Chiu, C.C., 2009. Financial time series forecasting using independent component analysis and support vector machine. Decision Support Systems 47 (2), 115–125.

Ni, H., Yin, H., 2009. Exchange rate prediction using hybrid neural networks and trading indications. Neurocomputing 72 (13–15), 2815–2823.

Suykens, J.A.K., Vandewalle, J., 1999. Least squares support vector machine classifier. Neural Processing Letters 9 (3), 293–300.

Tang, B., Dong, S., Song, T., 2012. Method for eliminating mode mixing of empirical mode decomposition based on the revised blind source separation. Signal Processing 92 (1), 248–258.

Tay, F.E.H., Cao, L., 2001. Application of support vector machines in financial time series forecasting. Omega 29 (4), 309–317.

Van Gestel, T., Suykens, J.A.K., Baesens, B., Viaene, S., Vanthienen, J., Dedene, G., De Moor, B., Vandewalle, J., 2004. Benchmarking least squares support vector machine classifier. Machine Learning 54 (1), 5–32.

Vapnik, V., 1995. The Nature of Statistical Learning Theory, First ed. Springer-Verlag, New York.

Vapnik, V., 2000. The Nature of Statistical Learning Theory, second ed. Springer-Verlag, New York.

Vapnik, V., Golowich, S., Smola, A., 1997. Support vector method for function approximation, regression estimation, and signal processing. 2000 In: Mozer, M., Vapnik, V. (Eds.), The Nature of Statistical Learning Theory, Second ed. Springer-Verlag, New York.

Wang, S., Yu, L., Tang, L., Wang, S., 2011. A novel seasonal decomposition based least squares support vector regression ensemble learning approach for hydropower consumption forecasting in China. Energy 36 (11), 6542–6554.

Yu, L., Wang, S.Y., Lai, K.K., 2008. Forecasting crude oil price with EMD-based neural network ensemble learning paradigm. Energy Economics 30 (5), 2623–2635.

Zhang, G.P., 2001. An investigation of neural networks for linear time series forecasting. Computers and Operations Research 28 (12), 1183–1202.

Zhang, G., Patuwo, B.E., Hu, M.Y., 1998. Forecasting with artificial neural networks: the state of the art. International Journal of Forecasting 14 (1), 35–62.