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Comparison of Back Propagation Neural Networks and EMD-Based Neural Networks in Forecasting the Three Major Asian Stock Markets

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Abstract: Recently, applying the novel data mining techniques for financial time-series forecasting has received much research attention. However, most researches are for the US and European markets, with only a few for Asian market. This study applies Back Propagation (BP) neural networks and Empirical Mode Decomposition (EMD) based neural networks for three Asian stock markets. In this study, an EMD-based neural network ensemble learning paradigm is proposed for three Asian stock market indices forecasting. For this purpose, three forecasting models are introduced in this study as follow: ANNs, the combination of EMD and ANNs, the combination of ANNs and EMD with parallel data input, the highest price, the lowest price and the close price. The three Asian stock market indices series are first decomposed into a finite and often small number of Intrinsic Mode Functions (IMFs) by introducing EMD function. Then a three-layer feed-forward neural network model is used to model each of the extracted IMFs, so that the tendencies of these IMFs could be accurately predicted. Finally, the prediction results of all IMFs are combined with a neural network to formulate an ensemble output for the three Asian stock market indices, respectively. The present experimental results show the superiority of the third model, compared to the previous two models.

Key words: Financial forecasting, BP neural networks, EMD, Asian stock market, ensemble learning

INTRODUCTION

Individual investors, stock fund managers and financial analysts attempt to predict price activity in the stock market on the basis of either their professional knowledge or with the assistance of stock analyzing tools. Higher accuracy is of paramount concern, since myriad profit will be made if more accurate predictions are given. Therefore, stock analysts have, perennially, strived to discover ways to predict stock price accurately.

In the past, most prediction models were based on conventional statistical methods, such as time-series and multivariate analysis. In recent years, however, Artificial Intelligence (AI) methodologies, including the Artificial Neural Networks (ANNs), Genetic Algorithms (GA) and fuzzy technologies, have become popular research models. They have been applied to many financial realms, including economic indices prediction (Van Gestel *et al*., 2001; Leigh *et al*., 2002; Teixeira and Rodrigues, 1997; Zhang *et al*., 2001), stock/futures price prediction (Kamijo and Tanigawa, 1990; Tay and Cao, 2001), currency exchange rate prediction (Qi and Zhang, 2001; El Shazly and El Shazly, 1999), option trading (Bailey *et al*., 1998), bond rating (Kim and Han, 2001; Shin and Han, 2001), bankruptcy prediction (Lee *et al*., 1996; Zhang *et al*., 2001) and portfolio optimization (Kosaka *et al*., 1991). These AI techniques were developed to meet the increasing demand for tools and methods that can predict, detect, classify and summarize the structure of variables and define the relationships between them B without relying too much on specific assumptions, such as linearity or on error distributions, such as normality. Many AI applications in the financial analysis have addressed this demand by developing the parametric non-linear models.

ANNs is a field of study within the AI area, where researchers employ a biologically inspired method to process information. They are good for solving some real-world problems especially in the areas of forecasting and classification decisions. However, most of the research has learning pattern limitations because of the tremendous noise and complexity of the input data. Some research indicates that the BP neural networks can perform very well in the financial time-series forecasting, for example, BP algorithms have been applied as alternatives to statistical techniques because of their superior accuracy. However, BP algorithm is a local search optimization method from the mathematical point of view.

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BP algorithm is likely to fall into local minima and leads training failed because of solving complex global extreme nonlinear function. In addition, the generalization ability declines with the improvement of training ability when the limit is reached. This is namely "over-fitting" phenomenon. In order to overcome the shortcomings of BP neural networks, we decompose the data with the EMD algorithm before we input the data into BP neural networks.

The Empirical Mode Decomposition (EMD) technique, proposed by Huang *et al.* (1998), is a form of adaptive time series decomposition technique using the Hilbert-Huang Transform (HHT) for nonlinear and non-stationary time series data. An Empirical Mode Decomposition (EMD) based neural network ensemble learning paradigm is proposed for world crude oil spot price forecasting by Yu *et al.* (2008). For better estimation of the impact of extreme events on crude oil price volatility, Zhang *et al.* (2009) attempted to use an EMD-based event analysis approach for this task. Xiong *et al.* (2013) proposed a revised hybrid model built upon Empirical Mode Decomposition (EMD) based on the Feed-forward Neural Network (FNN) modeling framework incorporating the Slope-based Method (SBM) which is capable of capturing the complex dynamic of crude oil prices. Cheng and Wei (2014) propose a hybrid time-series Support Vector Regression (SVR) model based on Empirical Mode Decomposition (EMD) to forecast stock price for Taiwan stock exchange capitalization weighted stock index (TAIEX) for promoting the forecasting performance of time-series models. Li and Huang (2014) employ the Hilbert-Huang Transform to investigate the multi-fractal character of Chinese stock market based on CSI 300 index. Li *et al.* (2008) used EMD method to analyze and discuss the structural properties of complex networks. The energy consumption in China 1953-2006 is estimated by applying the Energy Ecological Footprint (EEF) method and the fluctuation periods of annual China's per capita EEF (EEFcpc) growth rate are analyzed with the Empirical Mode Decomposition (EMD) method by Chen and Lin (2008). Qian *et al.* (2011) combined EMD with Detrended Fluctuation Analysis (DFA) and multifractal DFA. They find that the EMD-based DFA method performs better than the classic DFA method in the determination of the Hurst index when the time series is strongly anti-correlated and the EMD-based MFDFA method outperforms the traditional MFDFA method when the moment order q of the detrended fluctuations is positive. Zhang *et al.* (2008) applied Ensemble EMD (EEMD), an improved EMD, to crude oil price data and found that it can help interpret the formation of crude oil price from a novel perspective. Oladosu (2009) employed the Empirical Mode Decomposition (EMD) method to filter cyclical components of US quarterly Gross Domestic Product (GDP) and quarterly average oil price (West Texas Intermediate-WTI). Guhathakurta *et al.* (2008) have used the EMD technique to analyze two different financial time series, the daily movement of NIFTY index value of National Stock Exchange, India and that of Hong Kong AOI, Hong Kong Stock Exchange from July 1990 to January 2006. The returns of the two indices are shown to have strikingly similar probability distribution.

In this study, EMD and ANNs are used to present a financial time series forecasting model for three Asian stock market indices, 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 non-linearity and non-stationary limitations to the linear statistical model. Three forecasting models are introduced in this study as follow: ANNs, the combination of EMD and ANNs, the combination of ANNs and EMD with parallel data input-the highest price, the lowest price and the close price. The proposed approach of the combination of ANNs and EMD with parallel data input is compared with pure ANNs model and the combination of EMD and ANNs model and it is shown that the proposed model can yield more accurate results. Three financial time series are used as illustrative examples, as follows: Japan NK index, Korea KO index and HongKong HS index.

MATERIALS AND METHODS

Empirical mode decomposition (EMD) is a nonlinear signal-transformation method developed by Huang *et al.* (1998). 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:

Step 1: Identify all the local maxima and minima of $x(t)$.

Step 2: Obtain the upper envelope $x_u(t)$ and the lower envelope $x_l(t)$ of the $x(t)$.

Step 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, $m_1(t) = [x_u(t)+ x_l(t)]/2$.

Step 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, then repeat steps 1-3 of the decomposition procedure to eventually find the first IMF.

Step 5: After obtaining 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. 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:

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

Model setting and analysis: This section introduces three prediction models of this study. Model one is pure ANNs, Model two is EMD-ANN and Model three is EMD-ANN-PR. The following content gives a brief interpretation of these models.

Model one: In this study multilayer Feed-forward Neural Networks (FNN) was used as a computational model to forecast the stock index. This model is model one as benchmark model and we abbreviate model one as ANNs. The neural network has three layers-the input layer, the hidden layer and the output layer. The number of neurons in the hidden layer is predefined to the range from 2-10 according to the experience. From the literature reviews, there are two major drawbacks in FNN forecasting models: (1) Specific assumptions are required for observations and those models cannot be applied to the datasets that do not follow the statistical assumptions and (2) Most time-series models utilize late day stock price as input variable in forecasting. However, there are many noises involutedly in raw data that are caused by changes in market conditions and environments. The traditional time-series models which use the noise raw data should reduce the forecasting performance. For these reasons above, forecasting models should decompose the noise raw data into simpler frequency components and highly correlation variables to improve forecasting accuracy. Then, the overall flowchart of the proposed model one is shown in Fig. 1.

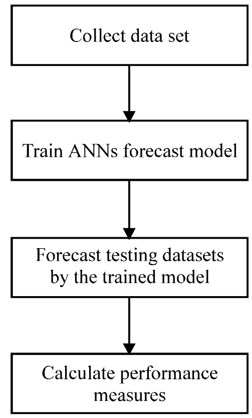

Fig. 1: Flowchart of model one

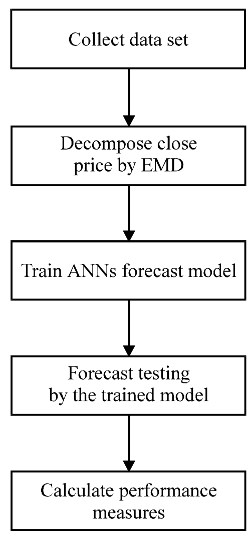

Fig. 2: Flowchart of model two

Model two: In order to overcome the above drawbacks, this paper considers that EMD can decompose the noise raw data into simpler frequency components and highly correlation variables. Then, the simpler frequency components will be refined by ANNs which can overcome the limitations of benchmark model and handle noise data involutedly. This model is model two and we abbreviate model two as EMD-ANN. Then, the overall flowchart of the model two is shown in Fig. 2.

Model three: The improvement of model two considering the correlation of the closing price, the highest price and the lowest price of the financial time series were carried out. The closing price, the highest price and the lowest price of the nonlinear and non-stationary time series into a sum of Intrinsic Mode Function (IMFs) components with individual intrinsic time scale properties we simultaneously decompose. Then the decomposition IMFs of the closing price, the highest price and the lowest

Table 1: Descriptive statistics of three Asian stock market indices

Index	No.	Mean	SD	Max	Min
Nikkei225 (NK)					
All sample	2287	12214.380	3018.895	18261.980	7054.980
Training	1830	12181.070	3123.335	18261.980	7054.980
Testing	457	12347.760	2557.034	16291.310	8365.900
KOSPI (KO)					
All sample	2320	1647.833	333.463	2228.960	870.840
Training	1856	1573.788	332.757	2228.960	870.840
Testing	464	1944.015	58.577	2059.580	1769.310
Hang Seng (HS)					
All sample	2333	20017.590	3612.351	31638.220	11015.840
Training	1866	19538.370	3839.292	31638.220	11051.840
Testing	467	21932.420	1309.628	24038.550	18502.340

SD: Standard deviation

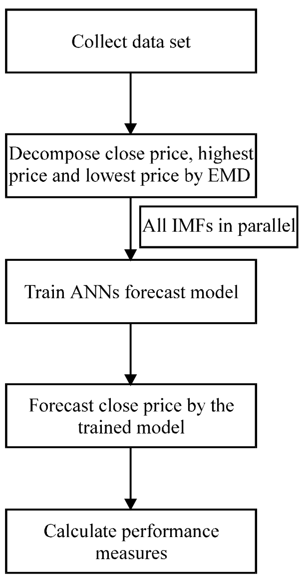

Fig. 3: Flowchart of model three

price will be refined by ANNs in parallel simultaneously to predict the close price. One can improve the prediction effect by the correlation of three time series-the close price, the highest price and the lowest price. This model is model three and it is abbreviated model three as EMD-ANN-PR (PR means in parallel). The overall flowchart of the proposed model three is shown as Fig. 3.

Historical data and statistical properties of the three asian indices

Data sets: It was examined that the three Asian stock market indices in the present experiment, namely the Nikkei 225 (NK)-Japan index, the Hang Seng (HS)-Hong Kong index and the KOSPI (KO)-Korea index. Data is collected from the RESSET financial database (www.resset.cn). The daily time series of three Asian stock market indices were studied from January 3, 2005 to April 8, 2014, with 3 components were studied: The highest, lowest and close prices. The data set was divided into two subsets: 80% of the data for training set and 20% of the data for testing set. The three Asian stock market indices statistical data are listed in Table 1 and the daily close prices used as the data sets are plotted in Fig. 4. The time periods cover many important economic events which we believe are sufficient for the training models.

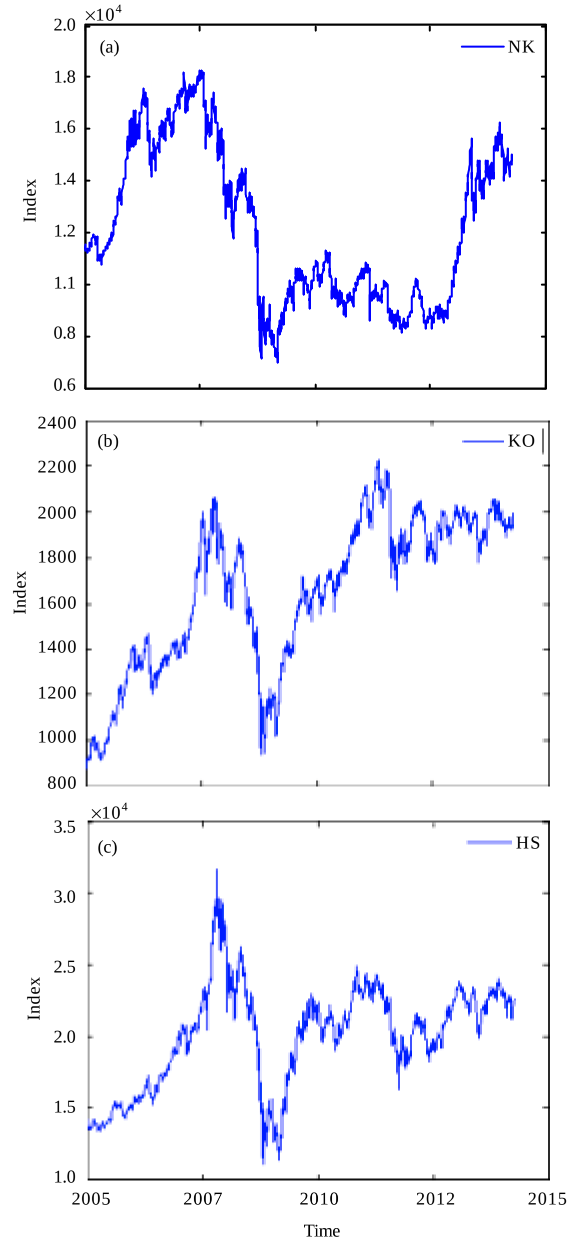

Fig. 4(a-c): Close price indices of three, (a) NK, (b) KO and (c) HS Asian stock markets

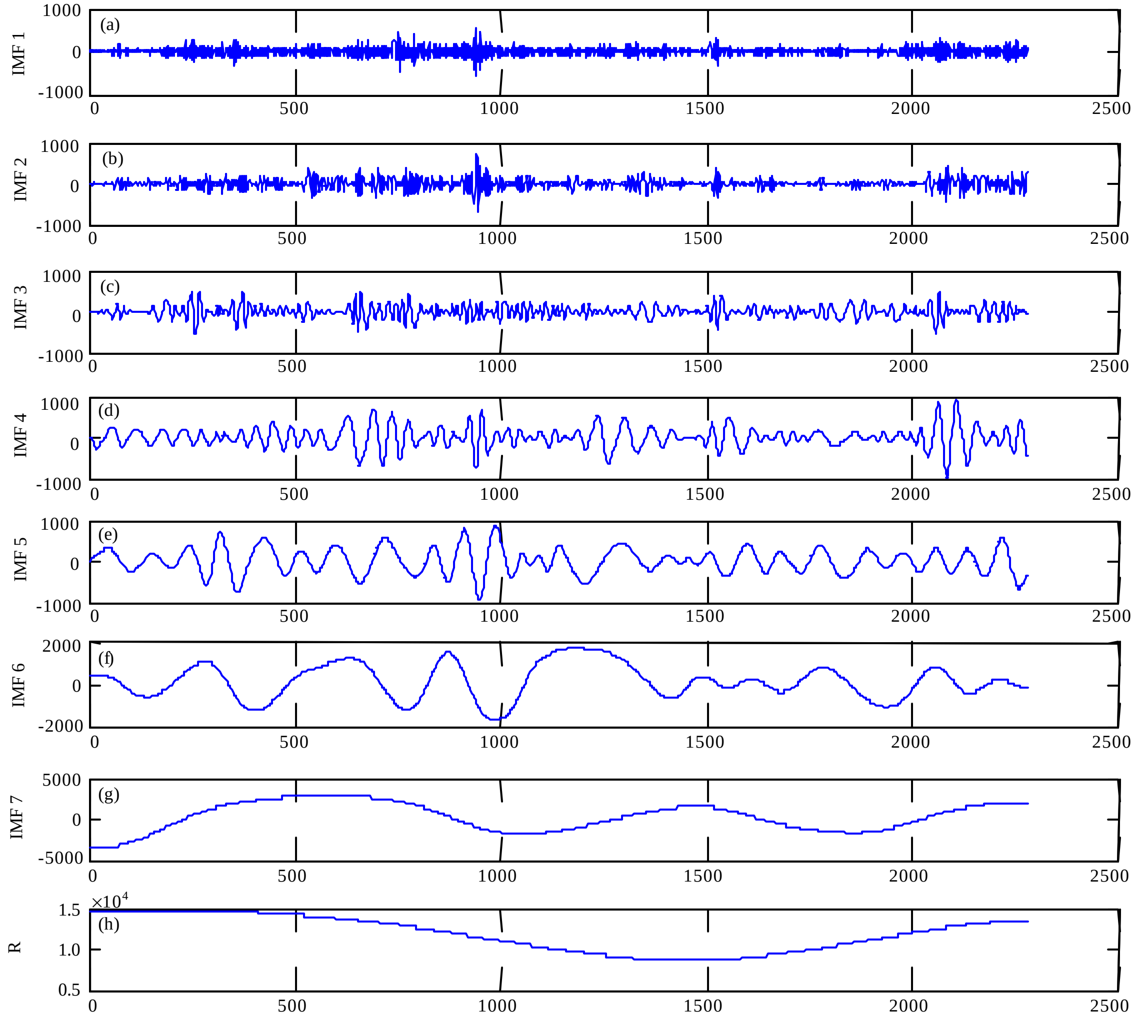

Fig. 5(a-h): Decomposition IMFs (a) IMF 1, (b) IMF 2, (c) IMF 3, (d) IMF 4, (e) IMF 5, (f) IMF 6, (g) IMF 7 and (h) R for close price of NK index

Decomposition IMFs of three Asian stock market indices: By definition the EMD method implies that the extracted IMF components are orthogonal, i.e., linearly independent. However, as noted by Huang *et al.* (1998) orthogonality depends on the decomposition method and is a requirement of linear decomposition systems, whereas the EMD is a non-linear method. Decomposition IMFs of three Asian Stock Market Indices are plotted in Fig. 5-7.

Performance measures to the prediction models: Following Lu *et al.* (2009) and Tay and Cao (2001), the following performance measures were 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 is 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. The DS provides the correctness of the forecasted direction of the stock market indices in terms of percentage, while CP and CD provide the correctness of the forecasted up trend and down trends of the stock market indices, also in terms of percentage. DS, CP and CD can be utilized to provide forecasting accuracy.

Table 2: Performance measures and their definitions

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

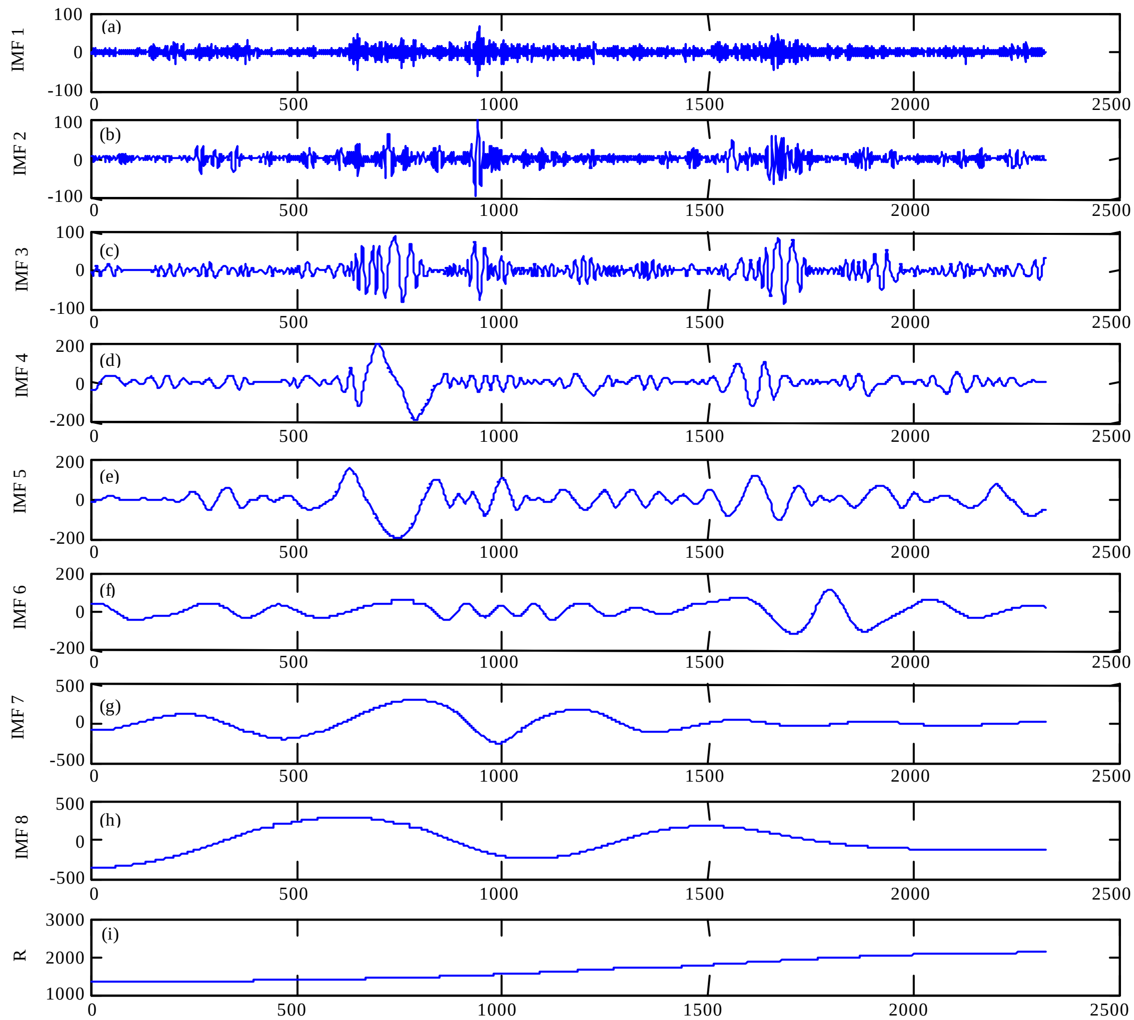

Fig. 6(a-i): Decomposition IMFs (a) IMF 1, (b) IMF 2, (c) IMF 3, (d) IMF 4, (e) IMF 5, (f) IMF 6, (g) IMF 7, (h) IMF 8 and (i) R for close price of KO index

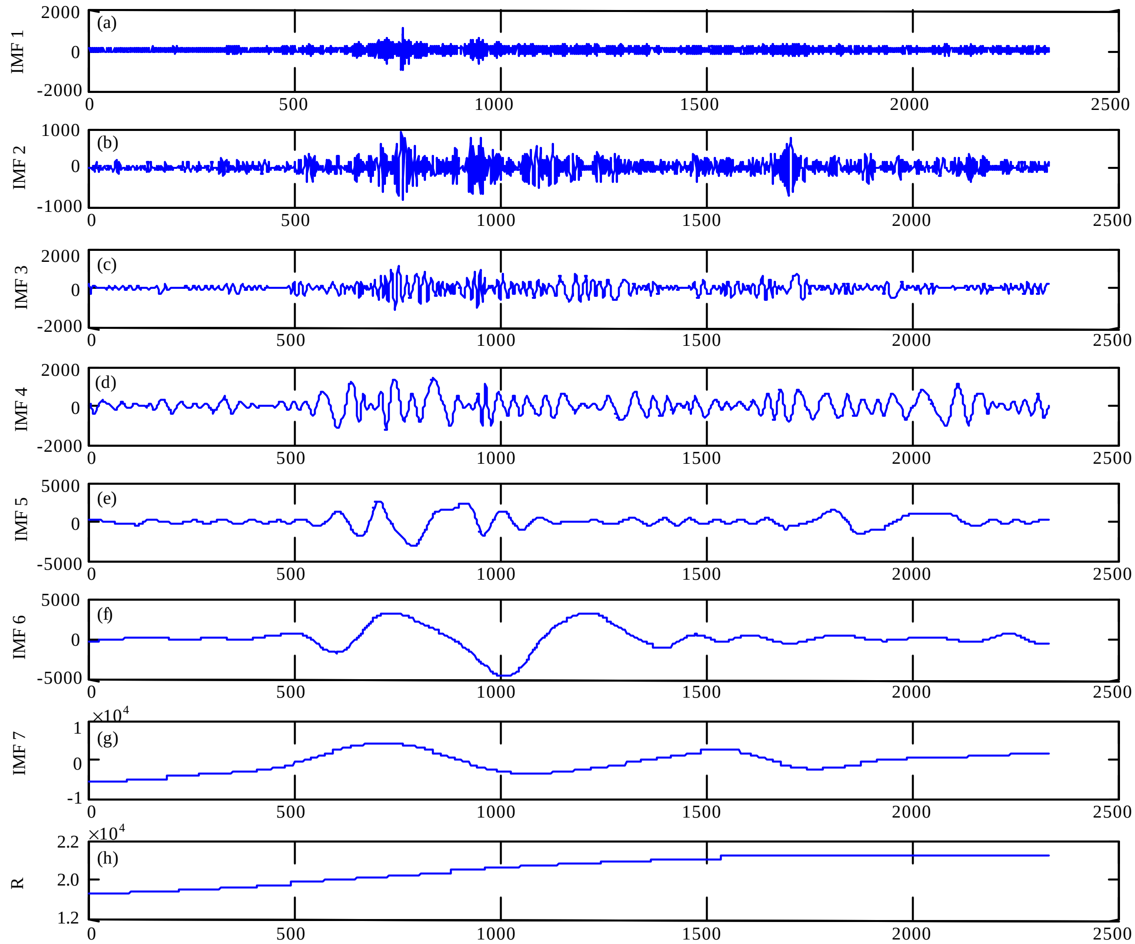

Fig. 7(a-h): Decomposition IMFs (a) IMF 1, (b) IMF 2, (c) IMF 3, (d) IMF 4, (e) IMF 5, (f) IMF 6, (g) IMF 7 and (h) R for close price of HS index

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.

RESULTS

Experimenting models and result interpretation: In order to analyze the model performance in a way closer to the investor's preference, we focus on prediction measures DS when analyzing the predicted results of various models.

Here, the forecasting results of the EMD-ANN-PR model are compared to pure ANNs model and EMD-ANN model. The first model is a hybrid forecasting model, one that integrates EMD with ANNs. The EMD is applied to decompose the three Asian stock market indices time series and gathered components that have a monotonic function, enhancing the forecasting ability of ANNs. Model one is the single ANNs without algorithms or treatments for forecasting. That is, the single ANNs are directly applied to forecast future stock market indices. 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-ANN and EMD-ANN-PR are shown in model setting and analysis. Using the EMD approach in the data decomposition, the three Asian stock markets indices time series can be decomposed into seven or eight independent IMFs and one residue component respectively, as illustrated in Fig. 5-7. These decomposition results may enhance the

Table 3: Indices forecasting results using EMD-ANN-PR, EMD-ANN, ANNs models

	Indicators					
Models	MAD	MAPE	RMSE	DS (%)	CP (%)	CD (%)
NK						
EMD-ANN-PR	163.4575	1.3561	208.2361	74.78	78.93	70.95
EMD-ANN	201.9704	1.6885	258.4718	73.95	78.42	68.57
ANNs	444.3296	3.7910	539.7942	55.88	59.92	51.64
KO						
EMD-ANN-PR	36.5246	1.8776	44.5787	73.97	73.64	76.47
EMD-ANN	43.9053	2.2538	48.4792	73.54	71.13	74.21
ANNs	182.8787	9.3868	186.7201	55.36	55.02	55.96
HS						
EMD-ANN-PR	198.9303	0.9127	239.1679	75.32	79.32	71.43
EMD-ANN	281.4580	1.2862	356.9951	73.43	76.47	70.54
ANNs	298.2232	1.3853	367.7995	56.64	59.74	53.74

Table 4: Percentage improvement of forecasting performance of the proposed EMD-ANN-PR model in comparison with other forecasting models

	Indicators (%)					
Models	MAD	MAPE	RMSE	DS	CP	CD
NK						
EMD-ANN	19.07	19.69	19.44	1.11	0.65	3.35
ANNs	63.21	64.23	61.42	25.27	24.08	
27.22KOEMD-ANN	16.81	16.69	8.05	0.58	3.41	3.03
ANNs	80.03	79.99	76.13	25.16	25.29	26.82
HS						
EMD-ANN	29.32	29.04	33.01	2.51	3.59	1.25
ANNs	33.29	34.12	34.97	24.80	24.68	24.77

model's forecasting ability in terms of the divide and conquer concept. Then, the decomposed forecasting variables, the independent IMFs and residual components from the previous step, are used in ANNs model construction. Parameter selection is essential for ANNs model construction. The number of neurons in the hidden layer varies from 2-10 according to experience. The look-back window length is an input parameter of the neural network which varies from 1-22 days.

The same EMD-based methodology steps are also fed into ANNs in order to build the hybrid forecasting model, namely, the EMD-ANN-PR model, the results of which are compared with those of the EMD-ANN model and pure ANNs model. The performance evaluation of each forecasting model is based on the several performance criteria from performance measures to the prediction models, as listed in Table 2. The performance measurements of the selected forecasting models are given in Table 3.

In order to verify the forecasting capability of the proposed EMD-ANN-PR model, the EMD-ANN and pure ANNs models are employed for comparison, using three Asian stock market indices data sets: (1) NK index data set, (2) KO index data set and (3) HS index 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-ANN-PR model as compared to EMD-ANN model and ANNs model. Take the NK index as an example, the forecasting results using EMD-ANN-PR, EMD-ANN and ANNs are computed and listed in Table 3, where it can be seen that the MAPE, RMSE and MAD of the EMD-ANN-PR model are 1.3561, 208.2361, 163.4575, respectively. These values are the smallest of all the forecasting models, that the deviation between actual and forecasted values in the EMD-ANN-PR model is the smallest. Moreover, EMD-ANN-PR also has higher DS, CP and CD ratios, 74.78, 78.93 and 70.95%, respectively. The DS, CP and CD provide a good measure of forecasting consistency of moving stock indices trends. In sum, it can be concluded that EMD-ANN-PR provides better forecasting accuracy and direction criteria for three Asian indices than EMD-ANN and ANNs. In addition, the results of EMD-ANN-PR are consistent with the principle of decomposition and ensemble. Time series decomposition may enhance forecasting ability. For example, in terms of DS indicators from the NK index forecasting, as shown in Table 4, relative to the comparison models, the improvement percentages of the proposed model are 1.11 and 25.27%, respectively.

The forecasting results and performance comparisons of the three forecasting models for the three Asian stock market indices are also reported in Table 3 and 4. In addition, It can be seen that the decomposition of time series in EMD can enhance the forecasting ability of ANNs model.

DISCUSSION

A new model, based on EMD model joining to fusion ANN procedure has been proposed to forecast stock price problems in three Asian stock markets. Furthermore, the proposed model is compared with two forecasting models, AR model (Box and Jnkins, 1976) and ANN model (Pan *et al*., 2005) to evaluate the performance of proposed model. An AR model (Box and Jenkins, 1976) is a representation of a type of random process and DS is approximately 50%; AR model is a special case of the more general ARMA model of time series. Pan *et al*. (2005) have investigated several aspects of input feature selection and the number of hidden neurons for a practical neural network for predicting Australian stock market index AORD. A basic neural network with limited optimality on these aspects has been developed which has achieved a correctness in directional prediction of 70%. After verification and comparison, the proposed method outperforms the listing methods. From the experimental results, there are two findings in this study as follows:

- It is evident that the proposed model is superior to the listing methods in terms of DS. The main reason is that the proposed model takes into account the EMD method with ANN for three Asian stock markets
- Parallel input can improve the forecasting performance slightly. EMD-ANN-PR outperforms EMD-ANN slightly on DS, CP and CD with 1.11, 0.65 and 3.35% in forecasting NK as Table 4 shows

CONCLUSION

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 study, an EMD-ANN-PR forecasting model is proposed. EMD is used to detect the moving trend of financial time series data and improve the forecasting success of ANNs. Through empirical comparison of several models of three Asian stock market indices forecasting, the proposed EMD-ANN-PR model outperforms EMD-ANN model slightly but outperforms pure ANNs model greatly on several criteria. Thus, it can be concluded that the proposed EMD-ANN-PR model may be an effective tool for financial time series forecasting.

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