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A combined neural network model for commodity price forecasting with SSA

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Abstract

Commodity price forecasting is challenging full of volatility, uncertainty and complexity. In this paper, a novel modeling framework is proposed to predict the market price of commodity futures. Three types of commodity are selected as representatives: corn from agricultural products, gold from industrial metal and crude oil from energy. We decomposed the original series into independent components at various scales using singular spectrum analysis (SSA). A SSA-causality test is introduced to investigate the mutual influence between commodity futures prices. Additionally, using the SSA-smoothing scheme, we construct combined neural network models including back propagation, radial basis function and wavelet neural network to predict the commodity price. The experimental results illustrate that neural network models with the SSA outperform the benchmarks in terms of distinct measures.

Keywords SSA · Neural network · Commodity price · Forecasting

1 Introduction

Commodity futures markets represent an important sector in global financial markets, and price forecasting accurately is of great interest to governments, enterprises and investors. Due to the lack of centralized spot markets for many commodities, futures markets often serve as the central platform for trading commodities. Commodity pricing depends greatly on the function of the futures market. Since commodities are closely related to the national economy and people's livelihood, price fluctuations attracted increasing attention. However, commodities, as a major investment, always have remarkable price volatility in the futures market. The American subprime mortgage crisis in 2008 and the European debt crisis in 2012 both caused excessive volatility in commodity prices. In addition, the uncertainty of the global economic situation and monetary policy, the aggravation of market speculation and other complex factors all contribute to the difficulties in forecasting commodity price. Therefore, accurate market forecasting is essential to financial and investment decision making, which can help the investors in reducing the risk caused by price fluctuation.

Traditional econometric and statistical models (Maghyereh 2004; Salisu and Oloko 2015; Zhang and Wang 2015), like autoregressive integrated moving average model, vector autoregression model and Markov regime switching model, had been employed to predict the economic time series. Due to the limitations of traditional methods, forecasting models based on artificial intelligence technique (AI) (Zhang and Wang 2015; Maghyereh 2006) were presented to characterize the nonlinear relationship of price series, like artificial neural network (NN) (Yu et al. 2008; Kristjanpoller and Minutolo 2015), support vector machine (SVM) (Zhang et al. 2015, 2017; Wen et al. 2017), and genetic algorithm (GA) (Motlaghi et al. 2008). Among the forecasting models, NN was widely used in predicting market prices. Zeng et al. (2010) proposed an improved back-propagation (BP) neural network based on projection pursuit optimization to get a high-precision simulation of gold futures prices. Zhang and Yong (2010) proposed a forecasting model of gold price based on wavelet neural network (WNN) and analyzed the main influence of gold price, and higher precision was achieved compared with BP neural network. The units and

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structure of WNN are determined by the wavelet analysis theory, avoiding the blindness of structural design in classical neural networks (Chen et al. 2006). Lin et al. (2010) proposed a price forecasting system for electric market participants to reduce the risk of price volatility by combining radial basis function (RBF) network and orthogonal experimental design.

To remedy the disadvantages of single methods, some studies showed that hybrid methods can obtain the better performances (Wang et al. 2005; Xu et al. 2015). Before forecasting technologies developed, numerous decomposition and constructional methods were presented: wavelet analysis (Reboredo and Rivera-Castro 2013), empirical mode decomposition (EMD) (Zhang et al. 2008), singular spectral analysis (SSA) (Vautard et al. 1992). SSA can be used as a time- and frequency-domain method for time-series analysis, independently from attractor reconstruction. SSA has been applied to many studies, such as climatological statistical diagnosis, quasi-periodic signal analysis and short-term climate prediction (Ding et al. 1998; Zhu et al. 2010). With the decomposition technique, the hybrid models can often achieve better performance.

In this paper, a neural network forecasting model based on singular peculiar analysis (SSA-NN) is presented. A SSA-causality test that can characterize the nonlinear causality is developed to analyze the mutual influence between commodity futures prices. We focus on three commodities: corn from agricultural products, gold from industrial metal and crude oil from energy. Based on the SSA technique, the decomposition of three commodity futures series is conducted and the smoothed commodity price series is fed into neural networks including wavelet NN, RBF NN and BP NN. The experimental results indicate that the combined neural network models perform better than the benchmarks.

This study is organized as follows: Section 2 introduces the methodology of the SSA-causality test and the SSA-smoothing-based NN forecast approach. Section 3 presents the simulation results and the discussion. The paper concludes with Sect. 4.

2 Methodology

In this section, the SSA-causality test and SSA-based NN framework are presented.

2.1 SSA-causality test

The classical Granger causality test depends on the right choice of the conditioning set and only considers linear prediction. The causality test based on SSA was proposed by Hassani and Thomakos (2010) that can effectively capture the nonlinear relationship between time series. It calculates the statistics based on the prediction accuracy of a nonlinear model (SSA and MSSA) and then performs a hypothesis test to determine the causal relationship between variables. The method can work with arbitrary statistical processes, whether linear or nonlinear, stationary or non-stationary, Gaussian or non-Gaussian.

Let X and Y be two different time series with the length T. To test whether the series Y is supportive for the forecasting the series X, the steps are as follows:

Step 1 Build a univariate SSA model of the series X and split 10% samples for computing forecasting errors.

Step 2 Compare the forecasting results of SSA with different parameters, select the optimal one as the final univariate SSA model. Let D_{X_t} correspond to the error series.

Step 3 Build a multivariate singular spectrum analysis (MSSA) model of series X and Y and split 10% samples for computing forecasting errors.

Step 4 Similarly, compare the forecasting effect of MSSA with different parameters, select optimal one as the final MSSA model, and let $D_{X_t|Y_t}$ correspond to the error series.

Step 5 Compute the test statistic S according to the obtained errors series:

$$S = \bar{D}\sqrt{\frac{n-1}{n \cdot \mathrm{var}(\bar{D})}} \tag{1}$$

where $D_t = D_{X_t|Y_t} - D_{X_t}$, $\bar{D}$ is the mean of D_t, $\mathrm{var}(\bar{D})$ is the variance of $\bar{D}$, and n is the number of samples.

Step 6 The S statistic follows the Students t-distribution with $(n-1)$ degrees of freedom under the null hypothesis $E(D_t) = 0$. The corresponding P value can be obtained from the t-distribution table. If the P value is smaller than 0.05, the series Y is supportive of forecasting the series X in the SSA-based test at a significance level of 0.05.

2.2 SSA-smoothing-based NN forecast approach

The SSA-NN is a combined approach combining singular spectrum analysis (SSA) and neural network (NN). The SSA is employed to decompose the original commodity futures price series into individual components. The smoothed series is reconstructed by excluding the noise components and fed into the neural network models.

2.2.1 SSA-smoothing

The SSA is applied to preprocess the commodity futures price series:

Step 1 For a one-dimensional time series $Y_T = (y_1, \ldots, y_T)$, set the window length L and compute the trajectory matrix X:

$$X = (x_{ij})_{i,j=1}^{L,K} = \begin{bmatrix} x_1 & x_2 & x_3 & \cdots & x_{T-L+1} \\ x_2 & x_3 & x_4 & \cdots & x_{T-L+2} \\ x_3 & x_4 & x_5 & \cdots & x_{T-L+3} \\ \vdots & \vdots & \vdots & & \vdots \\ x_L & x_{L+1} & x_{L+2} & \cdots & x_T \end{bmatrix}. \tag{2}$$

where $K = T - L + 1$, $(1 < L \leq N/2)$.

Step 2 Perform the singular value decomposition of the trajectory matrix X:

$$X = \sum_{i=1}^{d} \sqrt{\lambda_i} U_i V_i^T = \sum_{i=1}^{d} X_i. \tag{3}$$

Here, $d = L^*$, $L^* = \min(L, K)$. The set $\{\sqrt{\lambda_i} \mid \sqrt{\lambda_1} \geq \cdots \geq \sqrt{\lambda_d}\}$ is called the spectrum of the matrix X. The decomposition matrices $X_i = \sqrt{\lambda_i} U_i V_i^T$ have rank 1.

Step 3 According to the smoothing threshold, choose the first p decompositions with the contribution rate higher than the smoothing threshold.

(i) Perform diagonal averaging to transfer the decomposition matrix $X_i = (x_{l,k}^{(i)})_{l,k=1}^{L,K}$ into a time series $\widetilde{x}_i = (\widetilde{x}_1^{(i)}, \ldots, \widetilde{x}_T^{(i)})$:

$$\widetilde{x}_k^{(i)} = \begin{cases} \frac{1}{k} \sum\limits_{m=1}^{k} x_{m,k-m+1}^{(i)} & 1 \leq k < L^*, \\ \frac{1}{L^*} \sum\limits_{m=1}^{L^*} x_{m,k-m+1}^{(i)} & L^* \leq k < K^*, \\ \frac{1}{T-k+1} \sum\limits_{m=k-K^*+1}^{N-K^*+1} x_{m,k-m+1}^{(i)} & K^* < k \leq T. \end{cases} \tag{4}$$

where $L^* = \min(L, K)$, and $K^* = \max(L, K)$.

(ii) Sum the series $\tilde{x}_1, \ldots, \tilde{x}_p$ up, then obtain the smoothed commodity futures price series:

$$\tilde{x}_t = \sum_{i=1}^{p} \tilde{x}_i. \tag{5}$$

2.2.2 NN

(1) Back-Propagation Neural Network (BPNN) BPNN is a well-known feed-forward neural network; its network structure is trained by back-propagation algorithm. According to Kolmogorov's theorem, there always exists a three-layer back- propagation neural network to approximate the function in any desired degree of accuracy.

A three-layer BPNN consists of an input layer, one hidden layer and an output layer. Each layer is made up of units; the number of units in the hidden layer is arbitrary and usually determined by "trial and error." BPNN is fully connected, each unit is an input to all the units in the next forward layer, and none of the weights cycle back to the previous layer's output unit. Each connection has a bias θ_j and a set of weights w_{ij}, which connects unit i in the previous layer (denoted as I_i) to unit j. Then, the output O_j in the hidden and output layers can be computed as:

$$O_j = f\left(\sum_i w_{ij} I_i + \theta_j\right) \tag{6}$$

where $f(\cdot)$ is an activation function, and the symmetric sigmoid function and linear function are commonly used in the hidden layer and output layer. The error is propagated backward by back-propagation algorithm to update weights and biases.

(2) Radial Basis Function Neural Network (RBFNN) RBFNN is another kind of feed-forward neural network with one hidden layer, which applies the radial basis function as an activation function in the hidden layer. The output layer units are linear combinations of outputs in the hidden layer.

Let $X_i (i = 1, \ldots, m)$ be the input vectors of a network and $Y_j (j = 1, \ldots, n)$ be the outputs; the mapping relation between them can be defined as:

$$Y_j = \sum_i \omega_{ij} \rho(X_i, C_i), \tag{7}$$

where ω_{ij} are the weights connecting unit i in the previous layer to unit j, $\rho(X_i, C_i)$ are radial basis functions, and C_i are referred to as the centers of the radial basis functions. The radial basis function approach constructs an approximation based on the locations of data points. The Gaussian radial basis function is commonly used:

$$\rho(X_i, C_i) = e^{-\beta_i ||X_i - C_i||^2} \tag{8}$$

(3) Wavelet Neural Network (WNN) WNN is an artificial neural network based on wavelet theory. The network structure of WNN is basically the same as traditional back-propagation network, consisting of the input layer, hidden layer and output layer. The main difference is that WNN uses wavelet function as the excitation function. The process of the WNN is as follows:

Step 1 Decide the number of units in each layer: Set m nodes for the input layer, p nodes for the hidden layer, and n nodes for the output layer.

Step 2 Initialize the parameters: the initial wavelet stretch factor a_j, the translation factor b_j, the network connection weights (w_{ij} as the weight of the input layer to the hidden layer and w_{jk} as the hidden layer to the output layer), and the learning rate η.

Step 3 Input the training data x_k and the expected output d_k.

Step 4 Calculate the outputs of the hidden layer and output layer.

Step 5 Calculate the error and the gradient vector to update the parameters.

$$\begin{aligned} w_{jk}(t+1) &= -\eta \frac{\partial E}{\partial w_{jk}} + w_{jk}(t) \\ w_{ij}(t+1) &= -\eta \frac{\partial E}{\partial w_{ij}} + w_{ij}(t) \\ a_j(t+1) &= -\eta \frac{\partial E}{\partial a_j} + a_j(t) \\ b_j(t+1) &= -\eta \frac{\partial E}{\partial b_j} + b_j(t) \end{aligned} . \tag{9}$$

Step 6 Calculate the global error $E = \frac{1}{2}\sum_{i=1}^{n}(y_i(t) - d_i)^2$. Training stops when the error is small enough; otherwise, the iteration continues from Step 3.

2.2.3 SSA-NN forecast approach

Based on the SSA-smoothing technique, the smoothed series of commodity futures are obtained. Combining the original futures price series and smoothed series, we train the neural network models named SSA-NN. Let $x_t = (x_1, x_2, x_3, \ldots, x_n)$ be one of the commodity futures price series. The framework is shown in Fig. 1, and the forecasting process is as follows:

Step 1 Apply the SSA to decompose and reconstruct the smoothed series $\tilde{x}_t$.

Step 2 Choose the lag d of the series via the partial autocorrelation function (PACF) of x_t.

Step 3 Use $\tilde{x}_{t-1}, \tilde{x}_{t-2}, \ldots, \tilde{x}_{\mathrm{t-d}}$ as the input and x_t as the expected output, train and test the neural network to generate the forecasts.

The SSA decomposition technique tends to identify the general trend and different types of fluctuations of the series. Thus, it helps in extracting the real information and enables an improvement in decreasing the probability of overfitting.

3 Empirical results

Three monthly commodity futures price data are involved in the experiment. It ranges from March 1983 to December 2016: corn futures traded in the Chicago Board of Trade (CBOT), gold futures in the New York Commodity Exchange (COMEX) and WTI crude oil futures from US Energy Information Administration (EIA).

3.1 SSA-causality test

The SSA-causality test is employed to explore the relationship among three commodity futures (corn, crude oil and gold). The results of the SSA-causality test are exhibited in Table 1. The p values indicate whether the commodity futures in each row SSA-cause those in each column. For instance, a p value of 0.01319 means there is a SSA-causal relationship between crude oil and corn at the 5% level. That suggests that crude oil futures can help in explaining corn futures. With the information of crude oil futures market, one can better characterize the linear or nonlinear features of corn futures.

For corn futures, there is no doubt that agricultural prices have always been linked to crude oil prices. Crude oil prices have gone up continuously since 2003, bringing great pressure on the production of corn. Therefore, there is a SSA-causal relationship between the corn futures and crude oil futures. Table 1 clearly demonstrates that the gold futures can also offer information on the corn futures market. (The

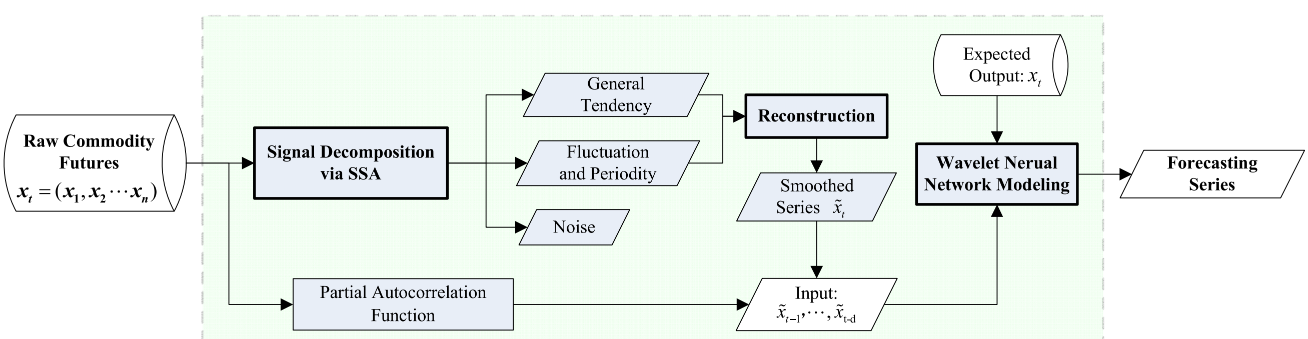

Fig. 1 Framework of SSA-NN

Table 1 Result of SSA-causality test

	Corn	Crude	Gold
Corn		0.06867*	1.00000
Crude	0.01319**		1.00000
Gold	0.07123*	0.01965**	
Corn + crude			1.00000
Corn + gold		0.22344	
Crude + gold	0.98928		

*10%; **5%; ***1%

p value is 0.07123.) However, it is observed that the combination of crude oil futures and gold futures has no significant effect on corn futures at the 1% level, which means the MSSA model using crude oil prices and gold prices does not perform better than the single-variable SSA model. For crude oil futures, gold futures is the SSA-causal of crude oil at the 5% level. However, there is no evidence showing that the combination of gold futures and corn futures can help in explaining the characteristics of crude oil futures. (The p value is 0.22344.) Finally, the price of gold is relatively stable since gold is a type of commodity used to hedge against inflation. The SSA-causality test results related to gold suggest that there is no SSA-causal relationship between gold futures and others.

3.2 Forecasting

The SSA-smoothing-based NN (WNN, BPNN, RBFNN) models are presented to forecast the monthly price of commodity futures. The sample data are split into two subsets with 90% of the data considered as the training subset and the most recent 10% of the data as the testing subset.

3.2.1 Forecasting model

Parameters For the SSA-NN model, the following parameters should be considered:

(1) The window length of SSA
(2) The smoothing threshold of SSA
(3) The number of nodes and the learning rate for NN
(4) The lags of the time series

The window length needs to be a multiple of the sequence period and should not exceed half of the data size. Since the common period of the three price sequences is 12 months, 24 is an appropriate choice of window length of SSA. Considering the model's efficiency, smoothing threshold is set to 0.02%, the number of hidden nodes is 15 and the learning rate 0.001. The lags of the series are investigated by the partial autocorrelation function (PACF). The first two lags are selected of crude oil, corn and gold series.

Smoothing with the smoothing threshold is 0.02%, and the first 10 components of corn futures are selected for the reconstruction, explaining 99.92% of the original series. The first nine components for crude oil futures and the first five components for gold futures are involved in the reconstruction, which explain 99.91 and 99.93% of the original series. Figures 2, 3 and 4 show the decompositions of three commodity futures and the contribution of each component. These decompositions represent the general trend, fluctuations and different periodicity of the price series separately. For instance, the price of corn futures began rising continuously in 2005 and started falling in 2012. The first component of corn futures explains 97% of the original series representing a general tendency. The economic crisis of 2008 and 2012 both has a great impact on the agricultural market. The violent fluctuations are characterized by the second component with a higher frequency. Furthermore, the remaining eight components represent the different periodicities of corn futures. By summing up these components, we can obtain the smoothed series of three commodity futures (Fig. 5).

3.2.2 Forecasting results and analysis

To evaluate the forecasting results of SSA-NN models, the baseline models are also introduced. Four performance evaluation criteria are investigated in this study. The mean absolute percentage error (MAPE), the mean absolute error (MAE) and the root mean squared error (RMSE) measure the deviation between the actual value and the forecasts. The directional change statistics (Dstat) examine the ability to catch changes in direction.

It is observed in Tables 2, 3 and 4 that SSA-NN outperforms NN models in most cases. For corn futures, RMSE, MAE and MAPE of the SSA-NN models are smaller than those of the baseline models, suggesting that the SSA-NN models are superior to baseline NN models. Additionally, the direction of change forecasts may be more important in economics for capturing business cycle movement. Note that the value of $Dstat$ for the SSA-NN models is much higher than that of the baseline models, which suggests that the SSA-NN models enable an improvement in capturing the changes in the trend. Thus, the SSA-NN models for corn futures outperform the baseline models. Similarly, the findings in Tables 3 and 4 also illustrate the superior performance of the SSA-NN models for crude oil futures and gold futures.

We take the SSA-WNN and WNN models as an example in further analysis. Figures 6, 7 and 8 show the forecasts (red) and the original series (blue) of the commodity futures. The in-sample forecasting results of the SSA-WNN and WNN models are both in satisfactory that they can capture almost

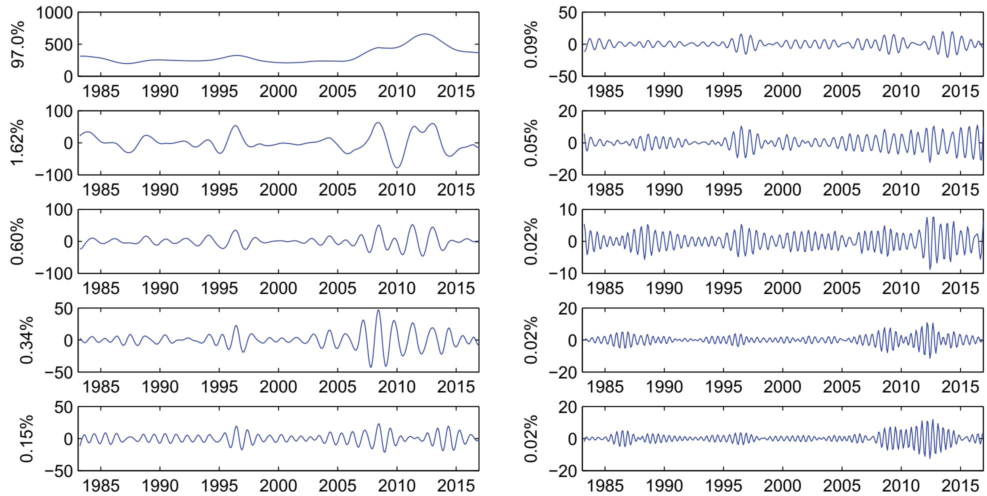

Fig. 2 Decomposition curves of corn futures

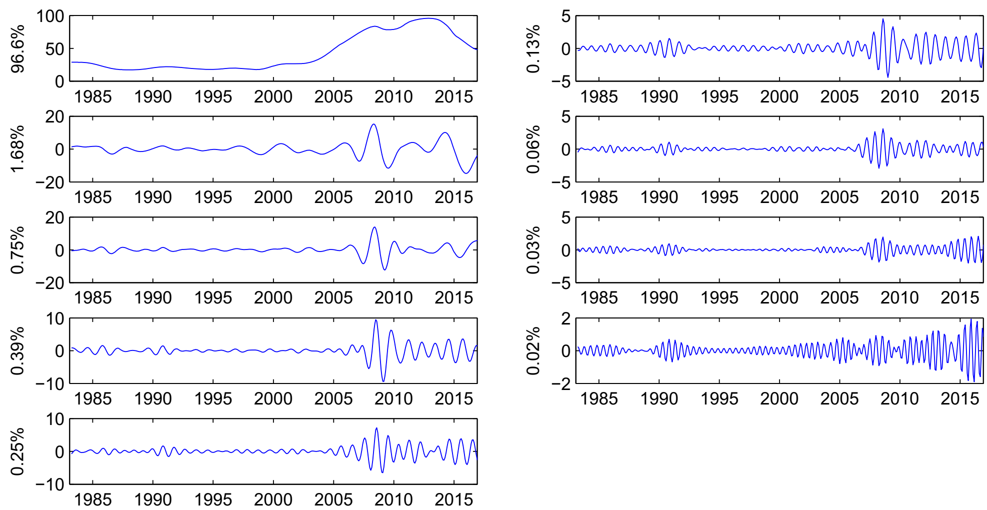

Fig. 3 Decomposition curves of crude oil futures

all of the changes of the series. The out-of-sample forecasting prices are the commodity futures from September 2013 to December 2016.

At the end of 2013, a large remaining supply led to a continuous decrease in corn futures until September 2014. As Fig. 6 shows, the SSA-WNN forecast of out of sample for corn futures is consistent with the actual situation. It also captures the local minimal corn futures around June 2015 and the downward trends over the next 8 months. In June 2016, Britain's exit from the EU and signs of improvement in the weather have some influence on the corn futures. The SSA-WNN model precisely captures this change in the trend. For crude oil futures, prices have gone down since July 2014. However, with the impact of the Asia-Pacific Economic Cooperation (APEC) held in November 2014, crude oil futures price rose for several months. Then, the crude oil price tended to downward until 2016 as the oil markets are

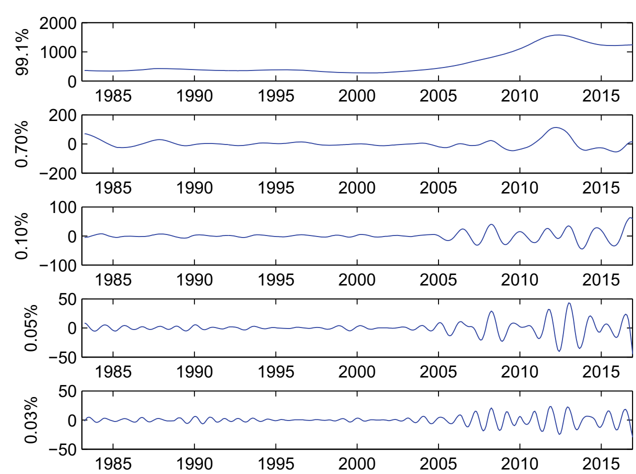

Fig. 4 Decomposition curves of gold futures

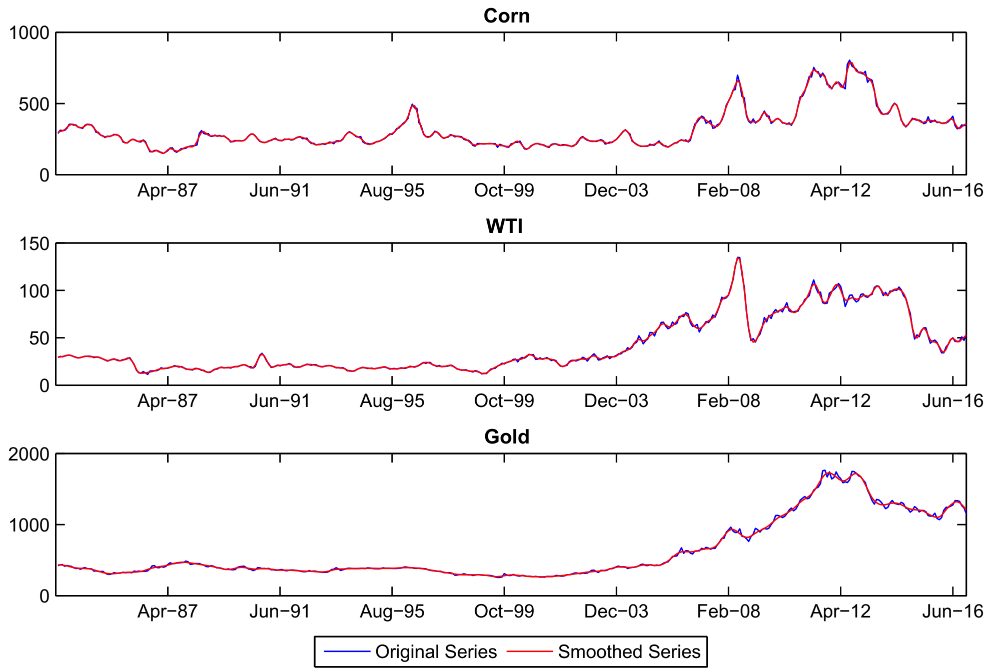

Fig. 5 Smoothed series of the three commodity futures

Table 2 Performance comparison for corn

	BP	SSA-BP	RBF	SSA-RBF	WNN	SSA-WNN
RMSE	31.086	20.602	23.656	17.292	28.445	24.329
MAE	21.576	15.173	17.556	13.169	21.053	18.026
MAPE(%)	5.469	3.839	4.540	3.341	5.428	4.618
Dstat	0.501	0.728	0.487	0.718	0.533	0.684

Table 3 Performance comparison for crude oil

	BP	SSA-BP	RBF	SSA-RBF	WNN	SSA-WNN
RMSE	5.797	3.506	5.346	3.493	6.405	5.754
MAE	4.528	2.818	4.172	2.895	4.903	4.397
MAPE(%)	7.999	5.183	7.318	5.249	8.757	7.970
Dstat	0.494	0.665	0.487	0.590	0.507	0.636

Table 4 Performance comparison for gold

	BP	SSA-BP	RBF	SSA-RBF	WNN	SSA-WNN
RMSE	57.063	50.724	47.657	36.855	56.489	52.922
MAE	46.728	42.005	38.578	30.301	47.686	45.135
MAPE(%)	3.839	3.458	3.190	2.503	3.913	3.721
Dstat	0.633	0.698	0.641	0.718	0.641	0.717

oversupplied. These trends are successfully characterized by the SSA-WNN model. For gold futures, there exists many small fluctuations in the out-of-sample series. The forecasts suggested that the general trend of gold futures is continuously decreasing until 2016.

Overall, we can conclude from the analysis above that SSA method can separate random noise from useful signals, thereby SSA-smoothing can further improve the forecasting performance of single neural networks.

3.3 Stability

In this section, we still use SSA-WNN and WNN models as an instance to analyze the model's stability. Considering

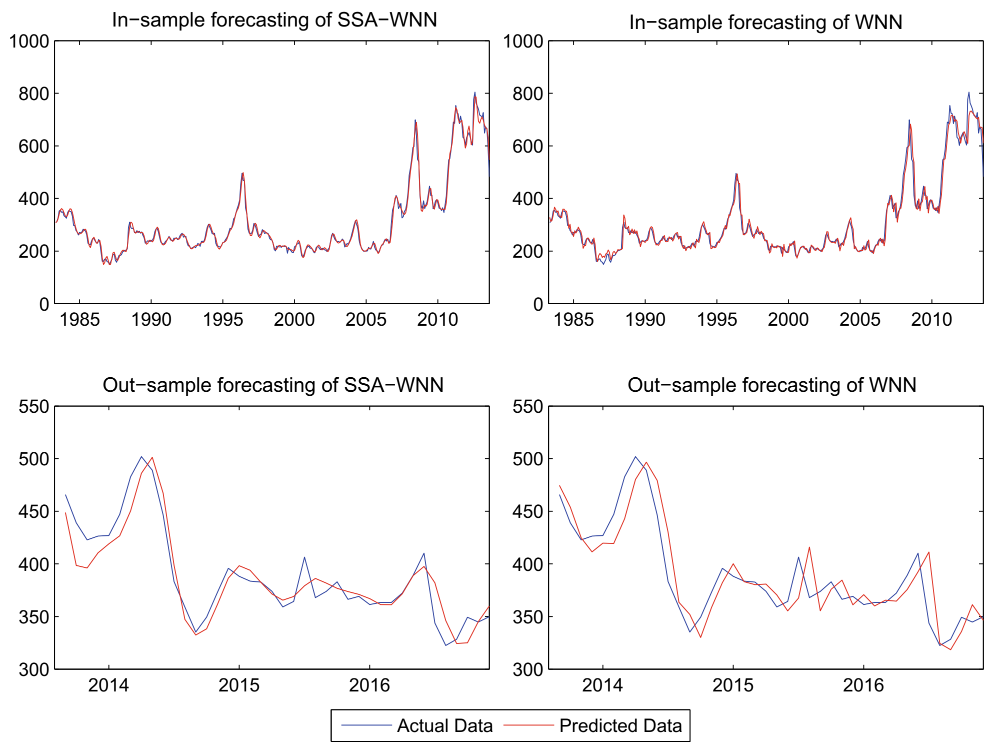

Fig. 6 Forecasts of corn futures

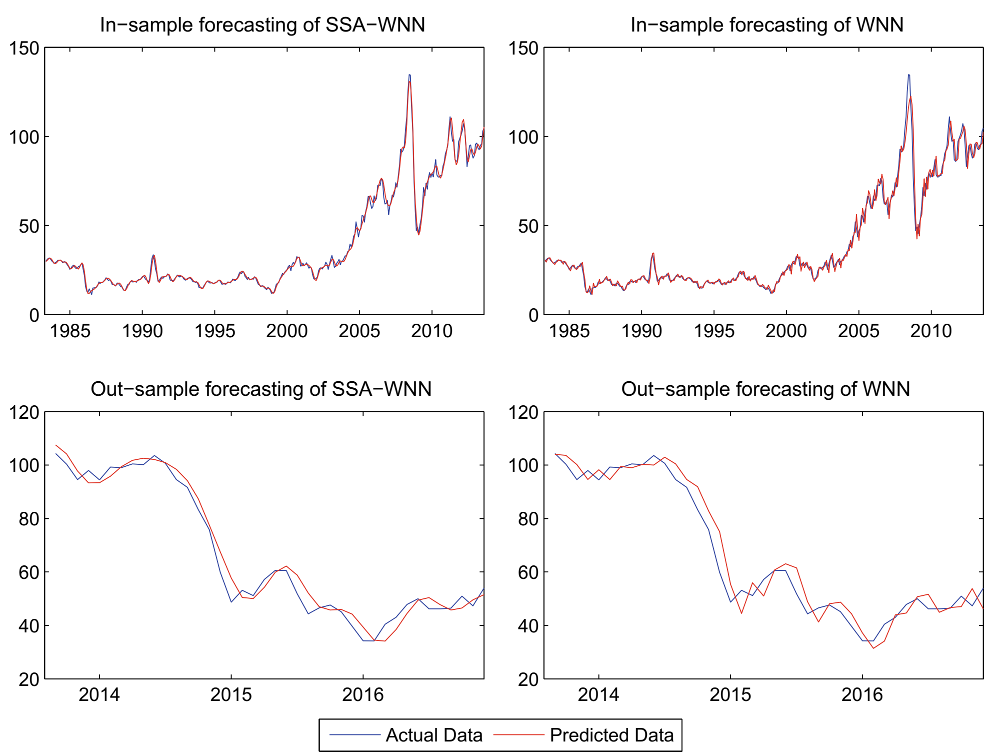

Fig. 7 Forecasts of crude oil futures

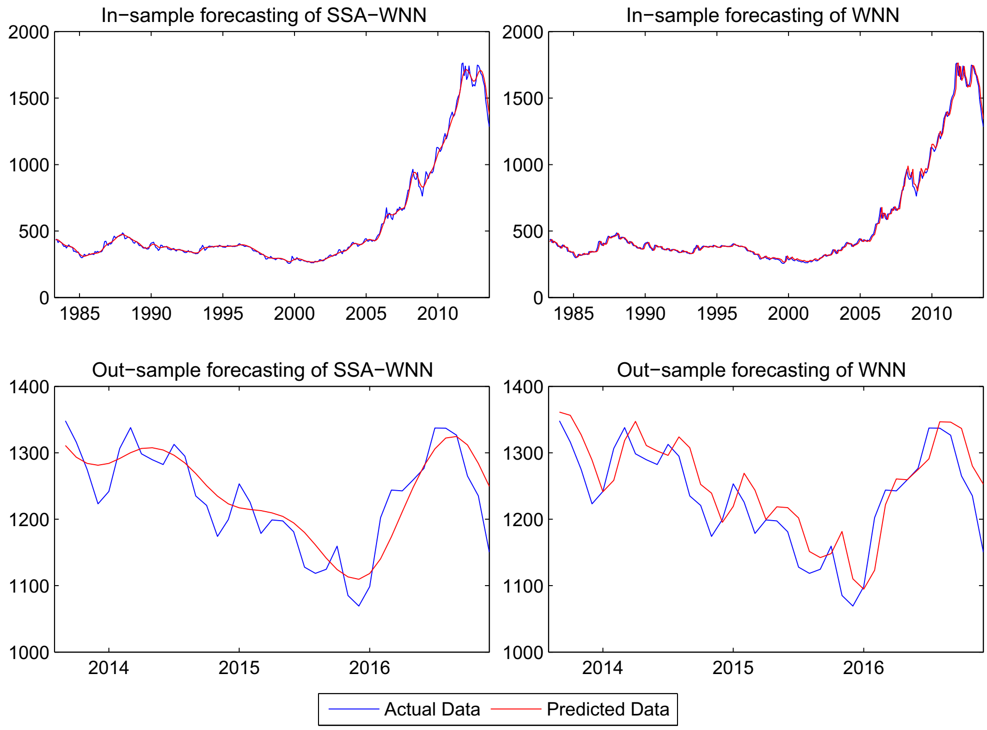

Fig. 8 Forecasts of gold futures

Table 5 The number of components at different thresholds

Threshold (%)	Corn	Crude oil	Gold
0.01	12	11	7
0.02	10	9	5
0.05	6	7	4

the number of components corresponding to the different smoothing thresholds, we choose 0.01%, 0.02% and 0.05% as the parameters to test. Table 5 shows the number of components at these thresholds of smoothing. As the window length of SSA decomposition is 24, the numbers of components for reconstruction under the three thresholds are available. For the nodes, we consider the setting of node number as 10, 15 and 20. Thus, forecasting models with nine combinations of these two parameters are introduced. The performance comparisons between SSA-WNN and WNN models are listed in Table 6.

It is observed that SSA-WNN models outperform WNN models with different parameters in most cases. The RMSE, MAE and MAPE of the SSA-WNN models for three commodity futures are smaller than those of WNN model. As for the direction forecasts, the Dstat shows that the SSA-WNN models also precisely capture the direction changes of price. There is only an exception with the SSA-WNN model under the 0.05% threshold and 15 nodes for gold futures. It may be attributed to the big smoothing threshold. As Table 5 shows, the smaller the threshold, the more components that are selected for reconstruction; otherwise, some valid information could be ignored. Since the gold futures price has been relatively stable and the noise in the price is less than that in other commodity futures, the threshold should be lower than corn and crude oil futures.

Table 5 demonstrates that the variation of thresholds will not affect the superiority of SSA-NN models unless the threshold is too large for the data. Hence, the SSA-Smoothing method is a promising method for the forecasting of commodity prices.

4 Conclusion

In this study, we presented a SSA-smoothing-based NN forecasting approach, aiming to improve the forecast accuracy and the ability to catch the change in trends. We compare the performance of the proposed approach to the baseline models using four criteria. Additionally, we analyze the causality relationship among three kinds of commodity futures.

The SSA-smoothing method decomposed the original series into individual components and separated the noise from valid information. The findings suggest that the SSA-smoothing-based NN models outperform the baseline NN model both in terms of accuracy and in terms of ability to capture the change in trends. The stability analysis indicated that the proposed approach has robustness and stable perfor-

Table 6 Performance of models with different parameters

Threshold	Corn				Crude oil				Gold			
	0.01%	0.02%	0.05%	WNN	0.01%	0.02%	0.05%	WNN	0.01%	0.02%	0.05%	WNN
10 nodes												
RMSE	28.70	26.84	30.06	31.98	5.75	6.16	5.93	6.62	60.22	59.30	65.91	68.17
MAE	21.62	20.11	23.03	23.35	4.32	4.74	4.60	5.08	53.09	51.39	56.34	58.43
MAPE (%)	5.56	5.17	5.95	6.00	7.87	8.56	8.16	9.06	4.35	4.23	4.65	4.79
Dstat	0.56	0.67	0.60	0.53	0.63	0.63	0.66	0.52	0.67	0.72	0.69	0.64
15 nodes												
RMSE	25.65	24.33	25.43	28.45	5.76	5.75	5.55	6.41	49.24	52.92	59.99	56.49
MAE	19.01	18.03	19.60	21.05	4.36	4.40	4.26	4.90	42.36	45.13	50.23	47.69
MAPE (%)	4.88	4.62	5.10	5.43	7.96	7.97	7.60	8.76	3.49	3.72	4.16	3.91
Dstat	0.57	0.68	0.62	0.53	0.63	0.64	0.67	0.51	0.67	0.72	0.69	0.64
20 nodes												
RMSE	26.63	26.21	25.44	28.28	5.63	5.80	5.37	6.39	55.02	55.97	54.88	61.67
MAE	19.63	19.78	19.32	20.85	4.24	4.43	4.13	4.94	47.80	47.88	44.84	52.55
MAPE (%)	5.03	5.08	5.01	5.36	7.66	8.00	7.29	8.76	3.94	3.95	3.71	4.31
Dstat	0.57	0.68	0.61	0.54	0.63	0.64	0.67	0.52	0.67	0.72	0.69	0.64

mance on a feasible threshold and number of hidden nodes in the neural network structure. Therefore, the SSA-NN method can be a promising tool to analyze and predict the price fluctuations. It can help decision makers and policy makers in formulating risk management strategies.

Note that the forecast is only based on historical price data in this study. In the big data era, internet concerns and investor sentiment expressed on the internet also lead to huge price volatility. Therefore, internet data related to the commodity market will be significantly considered to improve the forecast performance in future study.

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Compliance with ethical standards

Conflict of interest Authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

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