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A novel hybrid method for crude oil price forecasting

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ABSTRACT

Forecasting crude oil price is a challenging task. Given the nonlinear and time-varying characteristics of international crude oil prices, we propose a novel hybrid method to forecast crude oil prices. First, we use the ensemble empirical mode decomposition (EEMD) method to decompose international crude oil price into a series of independent intrinsic mode functions (IMFs) and the residual term. Then, the least square support vector machine together with the particle swarm optimization (LSSVM–PSO) method and the generalized autoregressive conditional heteroskedasticity (GARCH) model are developed to forecast the nonlinear and time-varying components of crude oil prices, respectively. Next, the forecasted crude oil prices of each component are summed as the final forecasted results of crude oil prices. The results show that, the newly proposed hybrid method has a strong forecasting capability for crude oil prices, due to its excellent performance in adaptation to the random sample selection, data frequency and structural breaks in samples. Furthermore, the comparison results also indicate that the new method proves superior in forecasting accuracy to those well-recognized methods for crude oil price forecasting.

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1. Introduction

Crude oil is a kind of indispensable basic energy source, chemical material and strategic resource in socio-economic development. The changes of crude oil prices may significantly affect economic development, social stability and even national security in a country (Wu and Zhang, 2014). Therefore, it is of great significance to design scientific methods to accurately forecast crude oil price movement as much as possible, so as to address crude oil market extreme risks and find profit-making opportunities.

However, due to the confluent influence of crude oil market supply and demand, US dollar exchange rate, speculative trading, geopolitical conflicts, natural disasters etc., international crude oil prices have boomed and plummeted within 30–150 dollars per barrel in the past decade, with extreme market risks (Zhang et al., 2008b; Zhang and Wei, 2011; Zhang, 2013). Historical data shows that the complex volatility characteristics of international crude oil prices, such as nonlinearity, uncertainty and dynamics, make crude oil price forecasting difficult and the forecasting results bear high uncertainties, which may eventually cause significant uncertainties for the returns of related investors and the steady development of social economy.

Moreover, it should be noted that the past literature about crude oil price forecasting often shows that crude oil price forecasting results are sensitive to the modeling sample interval selection, sample data frequency and sample structural breaks (i.e., outliers) etc. (Yu et al., 2008; Liu and Shi, 2013; Chen et al., 2014). As a result, it is a huge challenge for crude oil price forecasting work to design a reliable forecasting method to enhance the adaptability to these factors.

Under this circumstance, in this paper, we propose a new hybrid model for crude oil price forecasting, based on the advantages of econometric models and soft-computing methods in depicting the nonlinear, dynamic features of crude oil prices. Specifically, the new method for crude oil price forecasting is a hybrid of the ensemble empirical mode decomposition (EEMD), particle swarm optimization (PSO), least squares support vector machine (LSSVM) and generalized autoregressive conditional heteroskedasticity (GARCH) model. Meanwhile, in order to validate the robustness of the newly proposed method for crude oil price forecasting, we consider not only the randomness of sample selection, the frequency of sample selection (such as the daily, weekly and monthly observations), but also the adaptability to the structural breaks. In addition, we compare the new method with previously well-known methods in terms of crude oil price forecasting accuracy. The results show that the new method has a nice robustness faced with those sensitive factors and outperforms those popular methods with respect to forecasting accuracy.

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Table 1
Typical literature using the (G)ARCH type models to forecast crude oil prices or volatility.

Typical literature	Forecasting models	Main results
Sadorsky (2006)	Several GARCH type models	The TGARCH model is suitable for heating oil and natural gas while the GARCH model is appropriate for crude oil and unleaded gasoline.
Narayan and Narayan (2007)	GARCH model	Across the various sub-samples, there is inconsistent evidence of asymmetry and persistence of crude oil price shocks; and over the full sample period, the shocks have permanent effects, and asymmetric effects, on volatility.
Fan et al. (2008b)	GED-GARCH model	The GED-GARCH model has superior power in the out-of-sample forecast compared with the popular HSAF method.
Cheong (2009)	A series of ARCH models	An asymmetric long-term ARCH model has a higher forecasting ability for WTI market than Brent while in the Brent market, the GARCH model has the best forecasting performance.
Kang et al. (2009)	CGARCH and FIGARCH models	As for the WTI crude oil price volatility, CGARCH and IGARCH models are better than GARCH and FIGARCH models, respectively.
Wei et al. (2010)	GARCH models	There is not a model to win in all forecasts; however, overall the nonlinear GARCH model shows better forecasting power, especially for the long-term forecast.
Mohammadi and Su (2010)	GARCH, EGARCH, APARCH and FIGARCH models	In most cases, the APARCH model has better forecasting performance than other models.
Wang and Wu (2012)	GARCH models	The multivariate GARCH model has better forecasting performance than the univariate GARCH model overall, and the univariate GARCH model should be used if the crack spread is forecasted.
Hou and Suardi (2012)	Non-parametric GARCH model	The non-parametric GARCH model has a better forecast than the traditional GARCH model.
Arouri et al. (2012)	Three GARCH type models	Long memory is effectively present in all the series considered and a FIGARCH model seems to better fit the data, but the degree of volatility persistence diminishes significantly after adjusting for structural breaks.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents crude oil price forecasting methodology and data definitions. Section 4 puts forward crude oil forecasting results and some discussions. Finally, Section 5 concludes the paper and outlines the future work.

2. Related literature review

Crude oil price is the core of crude oil markets, and crude oil price forecasting proves an important determinant in the management of most industrial sectors across the world (Shin et al., 2013) and consequently becomes a hot spot in oil finance research. Up to now, there has been a raft of literature discussing crude oil price forecasting. Overall, previous literature mainly uses the econometric models (such as ARCH type model, VAR model), soft-computing models (such as neural networks, support vector machine) and wavelet technique. It should be noted that crude oil price forecasting methods have been increasing and forecasting performance has been improving in the past years. Here we would like to review related literature from the perspective of crude oil price forecasting methods, which may present a good foundation for the research in this paper.

First, there are a wealth of literature using the (G)ARCH type models to forecast crude oil price or its volatility and great progress has been achieved. This is mainly due to the fact the (G)ARCH type models have evident advantages in capturing the time-varying variance or volatility. Meanwhile, a body of literature compares the forecasting power of different types of ARCH or GARCH models (Fan et al., 2008b; Agnolucci, 2009). Some typical literature forecasting crude oil price or its volatility by means of the (G)ARCH type models are summarized in Table 1. It should be noted that the combined forecasting models between GARCH type models and other models, such as the implied volatility (IV) model, stochastic volatility (SV) model and support vector machine (SVM) model, tend to have superior performance. In fact, this is a promising trend for crude oil price forecasting. In other words, the hybrid forecasting models are more likely to be advocated in recent literature, which also gives some hints for our research in this paper.

Second, the neural network method has also been frequently used to forecast crude oil prices in recent years, which can be found in Table 2. It should be noted that the neural network method also has its evident disadvantages, such as over-fitting, local minima and weak generalization capability. Therefore, in the future research, the hybrid forecasting models incorporating the neural network method tend to be more appreciated. In fact, from existing related typical literature in Table 2, we have found this characteristic.

Third, the support vector machine (SVM) model has played a great role in crude oil price forecasting. Support vector machine is a new machine learning algorithm based on the statistical learning theory, and is particularly suitable for modeling with small sample size and nonlinear problems. [1]Due to the adoption of structural risk minimization (SRM) standards, SVM often has better learning performance and generalization capability compared to the traditional methods based on experience minimization. As a result, the SVM model has been extensively used for crude oil price forecasting, and some typical related literature are shown in Table 3.

Fourth, many scholars also try to forecast crude oil prices using the wavelet technique, which proves to have excellent performance in accuracy. For instance, the typical related literature shown in Table 4 basically testifies the merits of the wavelet technique in crude oil price forecasting. However, it also has some shortcomings in crude oil price forecasting. For instance, Yousefi et al. (2005) introduce a method based on the wavelet technique to forecast crude oil prices at four different time scales, i.e., 1 month, 2 months, 3 months and 4 months, and the results indicate that the wavelet technique is sensitive to the sample size. Therefore, how to avoid its sensitivity to the uncertain factors in modeling and enhance the forecasting robustness becomes a key issue for the wavelet technique.

In addition, a large number of studies use the hybrid method to forecast crude oil prices, which may combine the methods mentioned above. Some typical literature regarding the hybrid methods for crude oil price forecasting can be found in Table 5. Overall, the hybrid methods often imply the combination of interdisciplinary methods to use their strengths and can be roughly classified into three categories: (1) the combination among soft-computing methods, such as the intelligent optimization algorithms, EMD, SVM; (2) the combination among econometric methods, such as GARCH, ARIMA; and (3) the combination of soft-computing methods and econometric methods, such as the combination of GARCH type model and neural network method. These combining methods provide important hints for our study.

In summary, although international crude oil market proves a complex system, with rich multi-dimensional, nonlinear, dynamic features in crude oil price movement, the existing literature has accumulated a lot of experience in forecasting crude oil prices. In particular, the forecasting methods have been constantly emerging and the forecasting

[1] It should be noted that in industry, SVM does have been used to handle some machine learning problems in the big data environment.

Table 2
Typical literature using the neural network models to forecast crude oil prices.

Typical literature	Forecasting models	Main results
Yu et al. (2008)	The empirical mode decomposition (EMD) approach based on the neural network ensemble learning paradigm	The EMD approach outperforms other models, such as ARIMA model and FNN model.
Zhang et al. (2008a)	The artificial neural network (ANN) method, The Ensemble EMD (EEMD) method	The short-term fluctuations and long-term trends could be well forecasted by the support vector regression or ANN method.
Ghaffari and Zare (2009)	The adaptive neural network fuzzy inference system (ANNFIS)	The model has a good forecasting performance with relatively higher accuracy and reliability.
Movagharnejad et al. (2011)	The neural network method	The neural network methods are able to enhance the forecasting capability for all oil prices.
Wang et al. (2012)	A jump stochastic time effective neural network model	When the price volatility is weak, the forecasted value is closer to the actual value, and when the volatility appears large, the forecasted value may deviate from the actual value to some degree.
Azadeh et al. (2012)	A complex algorithm based on the ANN and fuzzy regression (FR)	The complex algorithm has better forecasting power than the ANN or FR alone.
Shin et al. (2013)	The combination of neural network method and machine learning algorithm	The new method significantly improves the forecasting accuracy compared with ANN, AR, SVM and other methods.

performance has been continuously improving. All of these provide an important foundation for the study in this paper. However, from the previous literature, we also find that the forecasting of crude oil prices still faces great uncertainties. For example, the results tend to be sensitive to the data frequency and sample range, and they may also have limited capability to capture the structural breakpoints in crude oil price series. These uncertainties have forged the serious challenges for crude oil price research and crude oil market regulations. In our opinions, these are mainly due to many factors affecting the movement of crude oil prices, such as crude oil production, economic growth, inventory level, production cost, geopolitical events, speculative trading and psychological expectation. The complex interaction of these factors makes crude oil price changing in a highly nonlinear and time-varying way, but the existing methods for crude oil price forecasting are usually not effective to separate nonlinear and time-varying components of crude oil prices and unable to extract their inherent moving mechanisms, which consequently affects the forecasting accuracy.

Therefore, in this paper, we may develop a hybrid forecasting method for crude oil prices given the complexity of crude oil markets. Specifically, we may employ the ensemble empirical mode decomposition (EEMD) model to decompose crude oil prices into a series of intrinsic mode functions (IMFs) and the residual. The EEMD model can decompose these featured components, i.e., IMFs, of crude oil prices in a hierarchical way. Then different models will be developed to handle different featured components. Meanwhile, the least square support vector machine together with the particle swarm optimization (PSO–LSSVM) method is used to forecast the nonlinear component and the GARCH model to forecast the time-varying component. Finally, the sum of forecasted values for all components is the final forecasted results of crude oil prices.

3. Crude oil price forecasting methodology

3.1. The EEMD method

The empirical mode decomposition (EMD), as a self-adaptive decomposition technique, has been proved quite effective in extracting characteristic information from non-stationary and nonlinear time series, like crude oil price series. The EMD approach has several evident advantages. For one thing, it can reduce any time series into simple independent intrinsic mode functions (IMFs). Second, its decomposition is based on the local characteristic time scale of the price series and only the extrema can be used in the sifting process, hence it is local, self-adaptive, concretely implicational and highly efficient. However, the EMD approach is not perfect and one of its major drawbacks is the mode mixing problem, which may cause the IMFs to be weak in the physical meanings (Zhu and Wei, 2011). To overcome the problem, the Ensemble EMD (EEMD) method was developed by Wu and Huang (2009), and the procedures of EEMD method can be described as follows:

(1) Initialize the number of ensemble (M) and the amplitude of the added white noise, with $i = 1$.
(2) Add a white noise series with the given amplitude to crude oil price series $X(t)$ as follows:

$$X_i(t) = X(t) + n_i(t) \tag{1}$$

where $n_i(t)$ denotes the ith added white noise series, and $X_i(t)$ represents the noise-added crude oil price of the i-th trial.

Table 3
Typical literature using the SVM models to forecast crude oil prices.

Typical literature	Forecasting models	Main results
Zhu (2007)	The SVM model	The SVM model has higher forecasting accuracy than the RBF neural network and ARIMA model.
El-Sebakhy (2009)	The SVM model	The performance of support vector machines is accurate, reliable, and outperforms most of the published models.
Liu and Ma (2008)	A novel forecasting model based on the Least Squared Support Vector Machine (LS-SVM)	The LS-SVM forecasting model outperforms the RBF network model.
Guo et al. (2012)	The GA-SVM forecast model, is based on genetic algorithm (GA) optimization parameters	The forecast efficiency of GA-SVM was better than that of traditional SVM.
Zhang et al. (2012)	An improved SVM model	The new model has significantly improved the forecasting accuracy.
Li et al. (2014)	The multi-faceted factor SVM model	The multi-faceted factor SVM has better forecasting performance than the SVM models combined with the error corrected model and the autoregressive regression model

Table 4
Typical literature using the wavelet technique to forecast crude oil prices.

Typical literature	Forecasting models	Main results
Liang et al. (2005)	The wavelet analysis method	Compared with the results using ARIMA and GARCH models, the forecasting performance of the wavelet technique proves significantly superior.
Ge et al. (2009)	A new algorithm based on wavelet analysis and Volterra self-adaptive filter method	The proposed method can effectively capture the dynamics of the nonlinear system series.
De Souza e Silva et al. (2010)	Wavelet analysis	This methodology might be a useful decision support tool for agents participating in the crude oil market.
He et al. (2012)	A semi-parametric wavelet decomposed ensemble model based on the heterogeneous market hypothesis	The new method has better forecasting accuracy than common algorithms and can also effectively simulate the time-varying heterogeneous market microstructure.
Reboredoa and Rivera-Castrob (2013)	Wavelet multi-resolution analysis	The oil price changes have no effect on stock market returns in the pre-crisis period at either the aggregate or sectoral level.
Shabri and Samsudin (2014)	A new method based on integrating discrete wavelet transform and artificial neural networks (WANN) model	The WANN model was found to provide more accurate crude oil price forecasting than individual ANN model.

(3) Decompose crude oil price $X_i(t)$ into J IMFs $c_{ij}(j = 1, 2, \ldots, J)$ using the EMD method, where c_{ij} is the Jth IMF of the ith trial and J is the number of IMFs.
(4) If $i < M$ then go to Step (2) with $i = i + 1$, and repeat Steps (2) and (3) again with different white noise series.
(5) Calculate the ensemble mean $c_j(t)$ of N trials for each IMF of the decomposition as the final result as follows:

$$c_j(t) = \frac{1}{N}\sum_{i=1}^{N} c_{ij}(t), i = 1, 2, \ldots, N, j = 1, 2, \ldots, J. \tag{2}$$

where $c_j(t)(j = 1, 2, \ldots, J)$ is the Jth IMF component using the EEMD method.

3.2. The PSO–LSSVM method

3.2.1. The LSSVM method

The LSSVM method is originally proposed by Suykens and Vandewalle (1999). The reason why we single out the LSSVM method is that the LSSVM regression algorithm can achieve the global optimization by solving a set of linear equations, which allows LSSVM to be faster than SVM (Iplikci, 2006). Suppose $\{(z_i, y_i)\}$ for $i = 1, 2, \ldots, l$ is a given training set of crude oil prices, in which l indicates the sample size, $z_i = (z_{i1}, z_{i2}, \cdots, z_{ia})$ is the input vector with a multiple variables, and y_i is the output variable. Then the decision function can be defined as:

$$y_i = w^T\phi(z_i) + b \tag{3}$$

where $\phi(\cdot)$ denotes the nonlinear function that maps the input space to a high dimension feature space, w represents the weight vector and b is the bias term.

As for the function estimation problem, the structural risk minimization is used to formulate the following optimization specification:

$$\begin{aligned} &\min \ \frac{1}{2}\|w\|^2 + \frac{c}{2}\sum_{i=1}^{l}\xi_i^2 \\ &s.t. \quad y_i = w^T\phi(z_i) + \xi_i + b, \quad i = 1, 2, \cdots, l \end{aligned} \tag{4}$$

where c represents the regularization constant and ξ_i denotes the training error.

According to the Kuhn–Tucker conditions (Kuhn and Tucker, 1950), the final result of the LSSVM method for function estimation can be described as:

$$y_i(z_i) = \sum_{i=1}^{l}\delta_i K(z, z_i) + b \tag{5}$$

Table 5
Typical literature using the hybrid methods to forecast crude oil prices.

Typical literature	Forecasting models	Main results
Fan et al. (2008a)	The generalized pattern matching method based on genetic algorithm (GPMGA)	The GPMGA method proves more accurate than the pattern modeling in recognition system (PMRS) and Elman network with its effectiveness and superiority, although the PMRS and Elman network methods are also effective and well-recognized in financial market forecast.
Yang et al. (2010)	A non-linear combination of the EMD and SVM model	The combined model has higher accuracy than the single SVM model or neural network.
Jammazi and Aloui (2012)	The combination of the multi-layer BP neural network (MPNN) with dynamic properties and Haar A trous wavelet (HTW) decomposition	More eligible forecasting power is found according to the wavelet oil price signal which appears to be the closest to the real anticipations of future oil price fluctuations.
Tang and Zhang (2012)	A multiple wavelet recurrent neural network (MWRNN) model	The hybrid model uses the wavelet technique to capture the multi-scale data characteristics and a real neural network to forecast crude oil prices at different scales. Then, based on the BP neural network, they combine the forecasted crude oil prices in different scales to get the final optimal forecasted crude oil prices, which proves to see a high forecasting accuracy.
Xiong et al. (2013)	An EMD model, based on the feed-forward neural network (FNN) and slope-based method (SBM)	The EMD–SBM–FNN model with MIMO (multiple input–multiple output) strategy has the best forecasting accuracy.
Bildirici and Ersin (2013)	The augmentation of linear GARCH, fractionally integrated GARCH and Asymmetric Power GARCH models with LSTAR type nonlinearity models, and the proposed models will be augmented with neural networks	The fractionally integrated and asymmetric power improvements among the GARCH family models provide better forecasting capability for petroleum prices, and the proposed models with learning algorithms of neural networks improve the simple GARCH models.

where the dot product $K(z, z_i)$ is known as the kernel function. This paper applies the radial basis function (RBF), which is a commonly used function regarding the nonlinear regression problems (Schölkopf et al., 1997; Keerthi and Lin, 2003). The RBF with a width of σ and the overall sample of z can be defined as:

$$K(z, z_i) = \exp\left(-0.5\|z-z_i\|^2/\sigma^2\right). \tag{6}$$

When using the LSSVM method with the RBF kernel function, the parameters σ and c should be established. This paper employs the PSO method to obtain the optimal parameters.

3.2.2. The PSO method

The PSO method is an evolutionary computational technique, which is based on the simulation of flocking and swarming behaviors of birds and insects (Eberhart and Kennedy, 1995). Compared to other evolutionary computational methods, it can efficiently find optimal or near optimal solutions to the problem under consideration. The PSO method uses a set of particles, representing potential solutions to the problem. Then each particle moves towards the optimal position, which can be found out by adjusting the direction of its previously best position and its best global position.

We can define each particle as a potential solution to a problem in a d-dimensional search space. $U_i = (u_{i1}, u_{i2}, \cdots, u_{id})$ is the current position of particle i, $V_i = (v_{i1}, v_{i2}, \cdots, v_{id})$ is the current velocity, $P_i = (p_{i1}, p_{i2}, \cdots p_{id})$ is the previous position, and $P_g = (p_{g1}, p_{g2}, \cdots p_{gd})$ is the best position among all particles. Then the best position of particle i can be computed by the following equations:

$$v_{id}^{k+1} = w\, v_{id}^{k} + c_1 r_1 \left(p_{id} - u_{id}^{k}\right) + c_2 r_2 \left(p_{gd} - u_{id}^{k}\right) \tag{7}$$

$$u_{id}^{k+1} = u_{id}^{k} + v_{id} \tag{8}$$

where v_i^k and u_i^k is the current velocity and position of particle i, respectively; w is called the inertia weight; c_1 and c_2 are two positive constants called acceleration coefficients; and r_1 and r_2 are two independently uniformly distributed random variables with the range [0, 1].

3.2.3. The PSO–LSSVM method

Since the parameters σ and c of the LSSVM method have great influence on the forecasting accuracy, the PSO method is selected as an optimization technique to optimize the parameters. This method is not hard to implement and there are few parameters to adjust.

Step 1 Initialize the parameters, such as the population of particles $N = 20$, $c_1 = c_2 = 2$, $w_{\max} = 0.8$, $w_{\min} = 0.2$.

Step 2 Evaluate the fitness for each particle. In this paper, the fitness function is defined as follows:

$$\text{Fitness} = \left[\frac{1}{N}\sum_{i=1}^{20}\left(\hat{y}_i - {y_i}^2\right)\right]^{1/2} \tag{9}$$

where y_i and $\hat{y}_i$ represent the actual and forecasted crude oil prices, respectively.

Step 3 Update the previous and global best fitness according to the fitness evaluation results.

Step 4 Update the velocity and position values for each particle until the stop conditions are satisfied. The velocity for each particle is calculated based on Eq. (7), and each particle moves to its next position according to Eq. (8).

3.3. The GARCH model

Since crude oil price series displays time-varying volatility, a GARCH model is singled out to capture the complex dynamic characteristics of crude oil price movement. According to Bollerslev (1986), a GARCH (p, q) model is expressed as follows:[2]

$$\begin{cases} h_t = \eta h_{t-1} + \varepsilon_t \\ \varphi_t^2 = \pi_0 + \sum_{i=1}^{s} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \varphi_{t-1}^2 \end{cases} \tag{10}$$

where h_t denotes the return series of crude oil prices, ε_t represents the error term, and φ_t represents the error variance. $s > 0$, $q \geq 0$, $\pi_0 > 0$, $\alpha_i \geq 0 (i = 1, 2, \cdots s)$, and $\beta_j \geq 0$ $(j = 1, 2, \cdots q)$.

3.4. The hybrid method for crude oil price forecast

International crude oil price series has the complex characteristics of nonlinearity and time variations. Thus, the hybrid method that has capability to model both nonlinearity and time variations can be a good strategy for crude oil price forecasting. Under this circumstance, the EEMD method is used to extract different components of crude oil price series, where the PSO–LSSVM model is used to forecast the nonlinear component and the GARCH model is applied for forecasting the time-varying component. By combining different models, different aspects of the underlying patterns of crude oil price movement may be well captured. The procedures of the proposed hybrid method can be summarized as shown in Fig. 1 and described as follows:

(1) The original crude oil price series is first decomposed by the EEMD method into a finite intrinsic mode functions (IMFs) and one residual series. Then the original crude oil price series can be represented as:

$$X(t) = \sum_{i=1}^{n} C_i(t) + R_n(t) \tag{11}$$

where $X(t)$ is the original crude oil price series, while $C_i(t)$ and $R_n(t)$ are the intrinsic mode functions and residual series, respectively.

(2) Observe the intrinsic mode functions $C_i(t)$ and residual series $R_n(t)$. If the intrinsic mode function presents the feature of time variation, then we may define it as $S_j(t)$, otherwise $N_i(t)$. Therefore, the original crude oil price series can be defined as:

$$X(t) = \sum_{i=1}^{m} N_i(t) + \sum_{j=m+1}^{n} S_j(t) + R_n(t) \tag{12}$$

where $N_i(t)$ and $S_j(t)$ denote the nonlinear component and time-varying component extracted from the original crude oil price series, respectively.

(3) The PSO–LSSVM model is built to forecast the future values of $N_i(t)$ and $R_n(t)$, respectively, and their forecasted results are defined as $\hat{N}_i(t)$ and $\hat{R}_n(t)$, respectively. Meanwhile, the GARCH model is used to forecast the future values of $S_j(t)$, and the forecasted result is defined as $\hat{S}_j(t)$.

(4) The final forecasted crude oil price series is obtained by composing the forecasted results of $\hat{N}_i(t)$, $\hat{S}_j(t)$ and $\hat{R}_n(t)$, which can be represented as follows:

$$\hat{X}(t) = \sum_{i=1}^{m} \hat{N}_i(t) + \sum_{j=m+1}^{n} \hat{S}_j(t) + \hat{R}_n(t) \tag{13}$$

where $\hat{X}(t)$ is the forecasted crude oil price series.

[2] In fact, we also tried other GARCH type models in the GARCH family, but based on the significance of coefficients and AIC values, we single out the GARCH (p, q) model in the end.

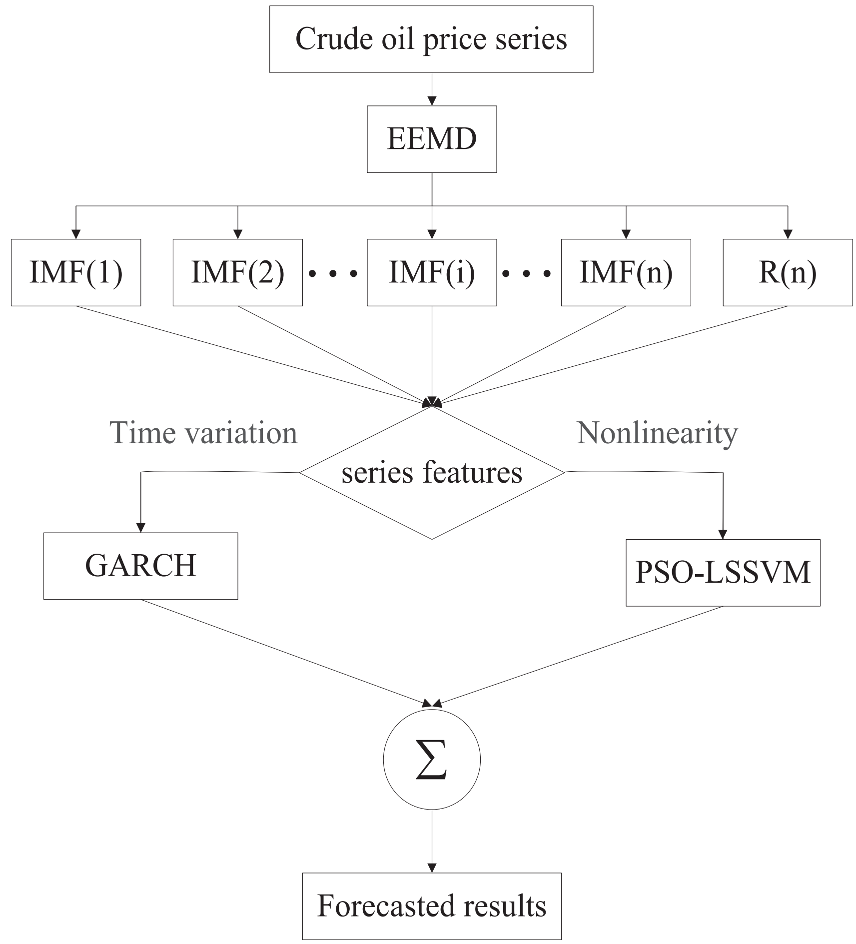

Fig. 1. The procedures of crude oil price forecasting using the new hybrid model.

Then several criteria are used to examine the forecasting accuracy of the newly proposed hybrid method. Specifically, the mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) are applied to evaluate the forecasting accuracy. The three criteria are defined as follows:

$$\mathrm{MAE} = \frac{1}{T}\sum_{t=1}^{T}\left|Q_t - \hat{Q}_t\right|, \tag{14}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Q_t - \hat{Q}_t\right)^2}. \tag{15}$$

$$\mathrm{MAPE} = \frac{1}{L}\sum_{t=1}^{L}\frac{\left|Q_t - \hat{Q}_t\right|}{Q'}, \tag{16}$$

$$Q' = \frac{1}{L}\sum_{t=1}^{L}Q_t, \tag{17}$$

where Q_t and $\hat{Q}_t$ denote the real and forecasted crude oil prices, respectively, and L is the number of observations used for forecasting performance evaluation and comparison.

4. Crude oil price forecasting result analyses

4.1. WTI crude oil price forecasting

(1) Daily crude oil price forecasting
The daily observations from January 2, 2013 to December 10, 2013 are used as the training samples, while those from December 11, 2013 to December 31, 2013 are considered as the testing samples. [3]According to the methods above, first, the original crude oil price series is decomposed by the EEMD method into six independent intrinsic mode functions and one residual, which are defined as sub-series in the following section. Fig. 2 shows the decomposition results using the EEMD method with the ensemble number 100 and the added noise amplitude 0.01 times standard deviation of the original series.
As shown in Fig. 2, the time variation behavior is observed in IMF1, IMF2 and IMF3, which is the high frequency component of the original crude oil price series, then the GARCH model is used to forecast these sub-series. For the other three sub-series, the PSO–LSSVM model is applied for forecasting. To demonstrate

[3] One reviewer argues that the time horizon of the training sample seems not long enough. In fact, there are 238 observations for training the model and 14 observations for testing the model. In the study of forecasting of crude oil prices or other commodity prices, we often select longer samples to develop or train the model and fairly shorter samples to test the forecasting capacity of the model. Besides, the support vector machine (SVM) model has superior performance in small-sample modeling. Therefore, the sample in this paper does not influence the forecasting capacity of the newly proposed model here.

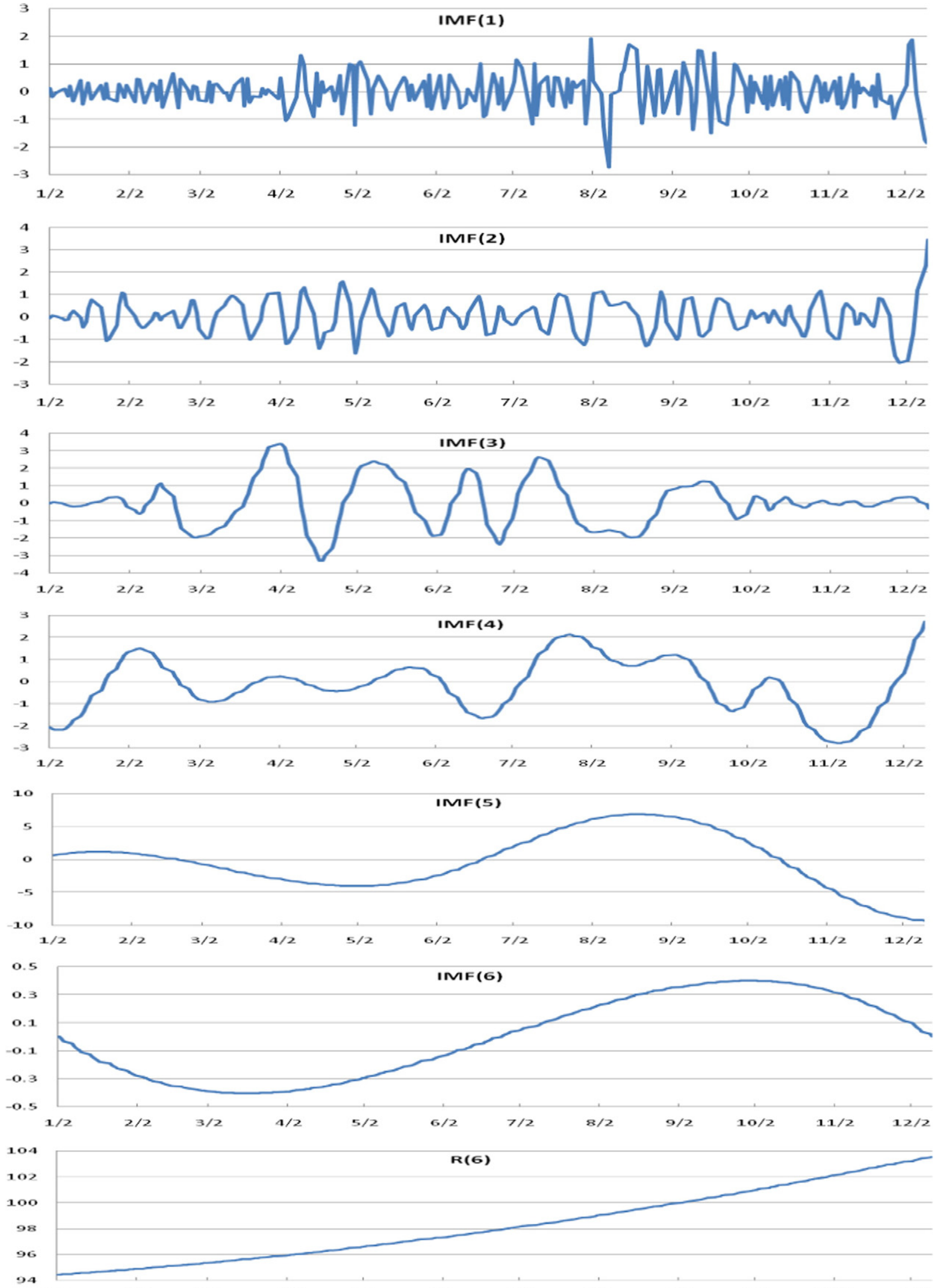

Fig. 2. The decomposition results of crude oil price series by the EEMD method.

the forecasting performance of the newly proposed method (Method 4), the EEMD plus GARCH method (Method 1), the EEMD plus PSO–LSSVM method (Method 2) and the PSO–LSSVM method (Method 3) are used as the comparative methods. Table 6 summarizes the comparative results of forecasting performance among the four methods.

Table 6
The errors of daily crude oil price forecasting using the four methods.

Time	Error criteria	Method 1	Method 2	Method 3	Method 4
2013/12/11	MAE	4.76	5.45	5.42	3.73
	RMSE	4.78	5.47	5.43	3.73
	MAPE (%)	4.89	5.36	5.12	3.85
2013/12/14	MAE	3.65	4.78	4.22	2.46
	RMSE	3.86	4.96	4.35	2.77
	MAPE (%)	3.76	4.81	4.28	2.54
2013/12/15	MAE	2.94	2.98	2.89	1.97
	RMSE	3.12	3.75	3.42	2.33
	MAPE (%)	3.00	3.69	3.34	2.03
2013/12/16	MAE	2.51	2.68	2.56	1.66
	RMSE	3.17	3.24	3.02	2.05
	MAPE (%)	2.58	2.79	2.68	1.71
2013/12/17	MAE	2.19	2.30	2.27	1.39
	RMSE	2.36	2.44	2.45	1.84
	MAPE (%)	2.27	2.33	2.30	1.43
2013/12/18	MAE	2.18	2.18	2.17	1.33
	RMSE	2.54	2.23	2.23	1.73
	MAPE (%)	2.13	1.97	2.05	1.37
2013/12/21	MAE	1.73	1.74	1.76	1.19
	RMSE	2.04	1.97	1.98	1.61
	MAPE (%)	1.86	1.87	1.86	1.23
2013/12/22	MAE	1.68	1.67	1.68	1.27
	RMSE	1.89	1.96	1.86	1.64
	MAPE (%)	1.79	1.77	1.78	1.31
2013/12/23	MAE	1.74	1.71	1.75	1.35
	RMSE	1.83	1.94	1.96	1.68
	MAPE (%)	1.75	1.73	1.74	1.39
2013/12/24	MAE	1.78	1.87	1.86	1.46
	RMSE	1.89	2.23	2.12	1.77
	MAPE (%)	1.82	1.98	1.90	1.51
2013/12/28	MAE	1.63	1.82	1.76	1.49
	RMSE	1.86	2.24	1.98	1.78
	MAPE (%)	1.79	1.99	1.89	1.54
2013/12/29	MAE	1.74	2.04	2.32	1.64
	RMSE	1.98	2.45	2.24	1.94
	MAPE (%)	1.78	2.02	1.90	1.69
2013/12/30	MAE	1.72	1.82	1.86	1.60
	RMSE	1.84	2.04	2.04	1.89
	MAPE (%)	1.73	1.88	1.80	1.65
2013/12/31	MAE	1.58	1.89	1.78	1.49
	RMSE	1.86	2.42	2.06	1.82
	MAPE (%)	1.63	2.06	1.84	1.53
Average	MAE	2.27	2.50	2.45	1.72
	RMSE	2.50	2.81	2.65	2.04
	MAPE (%)	2.34	2.59	2.46	1.77

As seen from Table 6, it is evident that the forecasting accuracy of Method 4 appears better than the other three methods, due to its lower MAE, RMSE and MAPE values. Specifically, compared with the average MAPE of Method 1 (2.34%), the average MAPE of Method 4 is only 1.77%. This result indicates that the PSO–LSSVM model has well captured the nonlinear features of crude oil prices. Also, the average MAPE of Method 2 is 2.59%, higher than that of Method 4. This implies that the GARCH model can well describe the time-varying volatility of crude oil prices during the sample period in this paper and then improve the forecasting performance. Besides, the average MAPE of Method 3 (2.46%) is also larger than that of Method 4, indicating its worse forecasting accuracy. This result shows that the EEMD method produces constitutive sub-series that can be forecasted more accurately than the original series. Overall, we can say that the forecasted results of Method 4 are reasonable and more accurate than the other three methods based on the daily observations.

(2) Weekly crude oil price forecast

As mentioned above, data frequency and structural breaks are important factors for the sensitivity of financial time series forecasting. Hence, to examine the forecasting robustness of Method 4, we also forecast WTI crude oil prices using the weekly observations. Meanwhile, in order to examine the forecasting performance regarding the crude oil prices with structural breaks, the observations of WTI crude oil prices from January 7, 2000 to May 30, 2008 are used for training, while the weekly observations from June 2008 to July 2008 for testing. The historical data show that the WTI crude oil prices in these two months reached the record high since 1986, but then began to fall abruptly, with clear structural break characteristics.

Under this circumstance, we aim to test the forecasting performance of the new hybrid method (i.e., Method 4) when the weekly observations and structural breaks are considered at the same time. Table 7 gives the errors of forecasted results among different methods, which indicate that the forecasted errors (MAE, RMSE, MAPE) of Method 4 can be acceptable, with small MAE and RMSE values and MAPE less than 3% through the testing sample period and the average MAPE 1.84%. Besides, the performance of Method 4 proposed in this paper is better than other three methods on average, due to its least average forecasted errors (2.48, 1.99 and 1.84% for MAE, RMSE and MAPE, respectively) compared with other three methods. Therefore, we may say that the new crude oil price forecasting method proposed in this paper has relatively reliable robustness with respect to the data frequency and structural breaks.

(3) Monthly crude oil price forecast

In the past studies, we often see that different selection of modeling (training) and testing samples may affect the forecasting performance of some methods, as mentioned above. To this end, we further use the monthly observations to test the robustness of the newly proposed forecasting method (i.e., Method 4) and try to verify its generalization capability. Put another way, we try to test the sensitivity of Method 4 to the sample selection. Therefore, we randomly select the monthly observations from January 1990 to December 2009, January 1991 to February 2011, January 1992 to December 2011 and January 1993 to June 2013 for training, while the monthly observations of January 2010, March 2011, January 2012 and July 2013 for testing.

Table 7
The errors of weekly crude oil price forecasting using the four methods.

Time	Error criteria	Method 1	Method 2	Method 3	Method 4
2008/06/06	MAE	0.29	0.45	0.35	0.29
	RMSE	0.28	0.46	0.34	0.29
	MAPE (%)	0.26	0.38	0.32	0.21
2008/06/13	MAE	2.78	4.67	3.14	2.06
	RMSE	3.34	4.81	3.56	2.71
	MAPE (%)	2.35	3.35	2.85	1.53
2008/06/20	MAE	2.98	4.42	3.64	1.74
	RMSE	3.78	5.01	4.05	2.31
	MAPE (%)	2.85	4.38	3.61	1.29
2008/06/27	MAE	4.12	5.98	5.04	2.05
	RMSE	4.33	6.21	5.12	2.50
	MAPE (%)	3.54	5.43	4.48	1.52
2008/07/04	MAE	4.98	8.10	6.42	2.77
	RMSE	5.13	8.64	6.87	3.36
	MAPE (%)	4.72	7.68	6.20	2.05
2008/07/11	MAE	6.23	10.2	8.41	3.22
	RMSE	6.34	10.5	8.49	3.79
	MAPE (%)	5.14	9.33	7.23	2.39
2008/07/18	MAE	5.06	11.2	7.98	3.71
	RMSE	5.83	11.8	8.57	4.33
	MAPE (%)	4.93	10.3	7.61	2.75
2008/07/25	MAE	5. 56	11.2	9.45	4.03
	RMSE	6.05	11.7	9.35	4.61
	MAPE (%)	4.76	10.3	7.53	2.99
Average	MAE	3.78	7.03	5.55	2.48
	RMSE	4.39	7.39	5.79	2.99
	MAPE (%)	3.57	6.39	4.98	1.84

Table 8
The errors of monthly crude oil price forecasting using the four methods.

Time	Error criteria	Method 1	Method 2	Method 3	Method 4
2010/01	MAE	2.43	2.05	2.43	1.20
	RMSE	2.43	2.05	2.43	1.20
	MAPE (%)	2.86	2.46	2.66	1.61
2011/03	MAE	4.76	5.64	5.38	4.36
	RMSE	4.76	5.64	5.38	4.36
	MAPE (%)	0.86	1.67	1.26	0.49
2012/01	MAE	1.48	1.86	1.86	0.50
	RMSE	1.48	1.86	1.86	0.50
	MAPE (%)	1.28	1.60	1.44	0.34
2013/07	MAE	1.97	2.11	1.96	1.81
	RMSE	1.97	2.11	1.96	1.81
	MAPE (%)	1.59	1.89	1.74	1.50
Average	MAE	2.66	2.92	2.91	1.97
	RMSE	2.66	2.92	2.91	1.97
	MAPE (%)	1.65	1.91	1.78	0.99

Table 8 summarizes the values of the three error criteria, including MAE, RMSE and MAPE, for forecasted results of the four methods, which show that the crude oil price forecasted errors using Method 4 can be acceptable. Specifically, the average MAPE is less than 2% in all of the randomly selected out-of-sample forecasting periods mentioned above. Furthermore, the forecasting performance of Method 4 is relatively better than that of the other methods, due to its lower average values of MAE, RMSE and MAPE, 1.97, 1.97 and 0.99%, respectively, although all the forecasting performances using the four methods are basically acceptable. In fact, we also find that in all the four forecasted months as shown in Table 8, Method 4 has the lowest MAE, RMSE and MAPE values all the time compared with other three methods. Therefore, we can say that Method 4 has favorable generalization capability in crude oil price forecasting. In other words, its forecasting power appears not much sensitive to the training and testing sample selection.

4.2. The forecasting accuracy comparison among different methods

To further demonstrate the robustness and superiority of the newly proposed method in this paper, we compare the forecasting accuracy of Method 4 with that of some well recognized methods proposed in previous literature. Meanwhile, we not only consider the forecast of WTI but also that of Brent crude oil prices. Besides, in order to obtain the objective comparative results, we take the same historical daily observations as previous literature for training and the same out-of-sample observations for testing the forecasting performance. Specifically, the daily observations of WTI and Brent for model training are from January 2, 1986 to June 24, 2005 and May 20, 1987 to June 24, 2005, respectively, while the daily observations from June 27, 2005 to July 26, 2005 are used for model testing, i.e., out-of-sample forecasting, and the MAPE values of forecasted results using different methods are shown in Table 9.

It should be noted that in order to verify the superiority of Method 4, we consider three well recognized forecasting methods, i.e., Elman network, pattern modeling and recognition system (PMRS) and generalized pattern matching based on genetic algorithm (GPMGA). Elman network has been proved to be effective and applied as a benchmark method in the research of Kermanshahi and Iwamiya (2002) and Kodogiannis and Lolis (2002) for energy market forecasting and financial market forecasting, respectively. Meanwhile, the main point of PMRS is to model the current pattern of a time series by directly matching its current pattern with past pattern, and then a forecast can be made according to the pattern following the most similar past pattern (Singh, 2001; Singh and Fieldsend, 2001). Besides, The GPMGA method is proposed by Fan et al. (2008a) to conduct a multi-step forecasting of crude oil prices. In the GPMGA method, the past pattern most similar to the current pattern is searched from historical observations to forecast future prices according to the historical rules represented by the matched past pattern. The GPMGA method overcomes some defects of PMRS and Elman network in the forecasting of long-memory time series (Fan et al., 2008a). Therefore, for the most part, the comparison of forecasting accuracy among Method 4 in this paper and the three methods above can verify the superiority of Method 4, with the same training and testing samples, if the forecasted results of Method 4 prove to have less MAPE values.

Table 9
The MAPE (%) of crude oil price forecasting using different methods.

	Elman network	PMRS	GPMGA	Method 4
WTI	2.59	2.24	1.57	1.27
Brent	3.23	2.93	2.43	1.53

Note: The details of Elman network, PMRS and GPMGA methods are well explained in Fan et al. (2008a).

Fortunately, as can be seen from Table 9, the forecasted errors (MAPE) of Method 4 for both WTI and Brent crude oil prices can be acceptable, which are less than 2%. Meanwhile, the forecasting performance of Method 4 proves superior to the other three benchmark forecasting methods no matter for WTI or Brent crude oil prices, due to its lower MAPE values, although the other three methods also have acceptable MAPE, which are less than 4%. Therefore, according to the comparative results, we can say that Method 4 in this paper indeed has relatively better forecasting performance for crude oil prices.

5. Conclusions and future work

Given the complexity of international crude oil price movement and the uncertainty of crude oil price forecasting results, this paper proposes a new hybrid method for crude oil price forecasting, which considers both the nonlinearity and time-varying dynamics of crude oil price movement. We test the performance of the new hybrid method when several common sensitive factors are concerned, which are popularly recognized previously, such as the random sample selection, sample frequency and sample structural breaks. In addition, we also compare the crude oil price forecasting accuracy using the newly proposed method in this paper and other three well recognized and extensively used crude oil price forecasting methods. In the end, several sound conclusions are drawn as follows.

First, the EEMD approach used in this paper may well separate the nonlinear and time-varying components of international crude oil price series, which is beneficial to model the different components of crude oil prices respectively afterwards and improve the forecasting accuracy.

Second, the PSO–LSSVM approach is able to effectively capture the nonlinear characteristics of crude oil price movement, while the GARCH model can well describe the time-varying characteristics of crude oil prices.

Finally, the newly proposed hybrid method has excellent forecasting performance for crude oil prices, regardless of the influence of random sample selection, sample frequency or sample structural breaks, which fully verify its good robustness and reliability. Additionally, the comparison of the new method and previously popular forecasting methods shows that the new hybrid method proves superior in crude oil price forecasting.

All of these results indicate the outstanding forecasting power of the newly proposed method for crude oil prices in this paper. However, it has to be pointed out that although the new hybrid method can well capture the complex dynamic behaviors of crude oil prices, its calculation process appears relatively complicated compared with most previous methods.

Overall, we may say that the new method for crude oil price forecasting provides a useful decision support tool for investors and analysts related with crude oil markets to evaluate crude oil price moving trends and then effectively measure extreme risk evolution dynamics. For instance, based on the IMFs, we can decompose the original crude oil prices into noise and signal components, which indicate the volatility and trend components, respectively. When the ratio of signal and noise components appears relatively small, the random movement of crude oil prices will be more evident and it is hard to capture the investing opportunities; but when the ratio becomes relatively large, the trend of crude oil price movement appears significant, which provides the good opportunities to make profits for the investors. Therefore, as long as the calculation process of the new method can be programmed and automated based on our codes attached, the investors and analysts can easily capture the market dynamics and deploy their resources to conduct some arbitraging activities and avoid market risks. Besides, the governmental regulators of crude oil markets can also obtain some sound policy recommendations to manage the market operations and avoid extreme events as much as possible, based on the forecasted dynamics of crude oil price movement.

It should also be noted that this paper employs the hybrid method to forecast international crude oil prices based on historical data. However, crude oil markets have proved to be a typical complex system, whose movement may be commonly affected by a number of factors, as mentioned above. Therefore, the accuracy of crude oil price forecasting is determined not only by the quantitative results from the hybrid method but also by some random variables which are hard to quantify. In this way, in the future, we may further consider the influence of those qualitative factors, so as to combine the quantitative and qualitative results and further enhance the forecasting accuracy.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2015.02.018.

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