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# A novel decompose-ensemble methodology with AIC-ANN approach for crude oil forecasting

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ABSTRACT

Forecasting international crude oil is a well-known issue. The hybrid modeling principle tells us that combining different methods could take full advantage of all the merits and leave out the shortcomings. Therefore, hybrid methodology has been widely used in current research. In this study, a novel decompose-ensemble prediction process combining the ensemble empirical mode decomposition (EEMD) and artificial neural network (ANN) is proposed. Moreover, this method, i.e., EEMD-ANN-ADD method, adds the decompose-ensemble to the single AI model to further improve the predicting accuracy. The overall process can be divided into four steps: model selection via Akaike's information criterion (AIC), data decomposition via EEMD, individual prediction via ANN and ensemble prediction through addition ensemble method. To verify the results, we use the official data of oil price to conduct the predicting. The result confirms that “decompose-ensemble” models are better than the normal hybrid one, in terms of prediction accuracy (both level and directional measurement) and modified Diebold-Mariano test. What's more, back to the decompose-ensemble models, the EEMD-based one outperforms the empirical mode decomposition (EMD) one. At last but not the least, AIC gives us reasonable and convincing statement about determining the value of lag. Generally speaking, this novel forecasting technique is a prominent insight for the price of crude oil.



## 1. Introduction

According to some recent published articles [1,2], energy market activities, especially the condition of international crude oil have significant effects on the world economic activities. The price of international crude oil fluctuates widely and it will directly affect the economy [3]. The oil price movements might result in inflation, economic depression or even political turmoil. Intuitively, we can draw the conclusion that predicting the crude oil price might become a vital topic in the academic field, which is in accordance with the actual condition. However, an abundance of literature has fully proved that the forecasting of crude oil is an extremely tough and challenge task [4]. It mainly because the affecting factors are various, ranging from economy, politics to sudden events. Both of the above mentioned effects are sometimes hard to measure. For these reasons, research on prediction of oil price is not meaningful but challenging tasks, the discussion about oil price attracts much attentions [5]. The forecasting methods includes the statistical and econometric models, artificial intelligence and hybrid modeling. Hybrid modeling, especially the “decompose-ensemble” method remarkably improves the prediction accuracy. However the original decomposition method itself has its drawbacks, such as mode mixing which would weaken the prediction accuracy. Moreover, researchers ignore to give reasonable statement about how to choose the proper model of crude oil price forecasting.

The objective of this paper is to build an effective decompose-ensemble procedure to forecast the oil price, i.e., AIC-based EEMD-ANN-ADD method. Based on some benchmark models and performance evaluation criteria, we prove the effectiveness and superiority of this method. To better understand the research progress of this problem, Section 2 thoroughly reviews and compares different methods. In Section 3, we execute empirical studies and proves that this novel method are better than the other ones. The materials, process, criteria and discussion are presented in this part. In the end, Section 4 covers the conclusions, limitations and future extensions.

## 2. Literature review

Crude oil is a kind of indispensable energy source, chemical

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materials and strategic resource in economic in a country's economic development. The price level related tightly to a country's economic development level, social stability and even political orderliness. The forecasting of international crude oil price is a famous widely discussed issue and there are abundant literature discussing around this topic. The existing method can be classified into three groups: traditional econometric, artificial intelligence (AI) and hybrid techniques [6].

The traditional econometric and statistic models cover many familiar models: Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) family [7–9], Autoregressive Integrated Moving Average Model (ARIMA) [10], co-integration analysis [11], vector auto-regression (VAR) [12], error correction models (ECM) [13] and other methods, like linear regression (LinR), naive random walk (RW) [14], grey model (GM) [15]. Related forecasting literature by means of econometric and statistic models are summarized in Table 1.

The methods listed are based on strict linear assumptions and the price series must be linear or near linear. In fact, the real data is always nonlinear and irregular, under which condition those techniques could not effectively capture the hidden nonlinear features [16]. That's why AI tools were proposed. The typical artificial intelligence tools are listed in Table 2 which include: Artificial neural networks (ANN) [17–21], support vector regression (SVR) [22–24], least squares support vector regression (LSSVR) [25] and other methods like genetic programming (GP) [26] and belief network (BN) [27]. Although the AI models could effectively pick out the nonlinear patterns in the time series, they still have their own shortcomings such as parameter sensitiveness, over-fitting and local minimum [16].

With the development of AI tools, the traditional econometric models, with their own shortcomings, still play irreplaceable role in analyzing the price condition in energy market [28]. Wang et al. [29] proposed model selection with parameter restricted model, which has been proved to improve the predictive accuracy and enrich the policy implication. Baumeister et al. incorporated more inputs into the predictive regression [3,30–34]. Moreover, in recent years other approaches have appeared in this context, including long memory and fractional integration approaches [35–37].

To overcome the disadvantages of single traditional statistical and AI tools, the concept of "hybrid modeling" was proposed. It tells us that a hybrid model gathers all the models' advantages and offsets the drawbacks, which leads to the widely use of hybrid models in the crude oil price prediction. Wang et al. [38] hybrid ANN and rule-based expert system, with web text mining, to forecast the oil price. Amin-Naseri and Gharacheh [39]. combined feed-forward neural networks (FNN), genetic algorithm, and k-means clustering, to predict the crude oil price and obtained great results. Chiroma et al. [26] combined genetic algorithm and neural network to predict the WTI crude oil price. Baruník and Malinská [40] hybridized regression method with ANN to analyze the term structure of oil price and get the lowest errors. In particular, the interactive inner factors would result in some noises which might corrupt the true oil price data and weaken the prediction accuracy. Inspired by integrating denoised methods into AI models to solve economic problems [41–47], Yu et al. [4] hybrid the denoising procedure, ie. compressed sensing based denoising (CSD), with AI models to forecast the crude oil price. Logically and thoroughly, they analyze the effectiveness, superiority and robustness of this novel model. The results of these studies have showed that the hybrid models are better than their respective single models, and intuitively confirmed that the hybrid models are effective.

Particularly, "decompose-ensemble" principle has been considered as an alternative helpful hybrid tool for analyzing the crude oil data which is highly complex and irregular [16,48]. Jammazi and Aloui [49]. combined multilayer back propagation neural network and wavelet decomposition to forecast the price of crude oil. Yu et al. [16] suggested a novel FNN-based decompose-ensemble prediction method for crude oil. He et al. [50] using wavelet-based decompose-ensemble methodology to analyze and predict the price of crude oil. Tang et al. [51] coupled the complementary EEMD and extended extreme learning machine (EELM) to research on the prediction of crude oil price. Yu et al. [6] proposed a novel data-characteristic-driven ensemble method to predict the price of international crude oil. Tang et al. [52] and Zhu et al. [53] integrated EEMD and LSSVR to predict complex price series with high volatility and irregularity. Similarly, Wang et al. [54]developed a two-layer decomposition hybrid model which combined EEMD, firefly algorithm and BP neural network to predict time series.Yang et al. [55] combined the wavelet transform, the kernel extreme learning machine and auto-regressive moving average to predict the electricity price fluctuation. As a specific occasion of hybrid modeling, the methodology of "decompose-ensemble" can remarkably improve the prediction.

According to the literature review, EEMD-based AI methods are very popular in recent years. However, there are many knowledge gaps waiting for us to fill. For example, only a few scholars discussed how to choose the proper model and pick up the most relative input time series [4]. It would be an improvement if we can apply a classical model selection method to the international crude

**Table 1**
Typical literature using the statistic and economic models to forecast crude oil prices.

| Typical literature | Forecasting models | Main results |
|---|---|---|
| Hou and Suardi [7] | Non-parametric GARCH model | The proposed GARCH model outperforms the traditional GARCH model. |
| Li et al. [8] | Component GARCH | Their forecasting model has better predictive accuracy than the GARCH and ARMA models. |
| Morana [9] | semiparametric GARCH model | The forecasting approach can be used to obtain a performance measure for the forward price, in addition to compute interval forecasts for the oil price. |
| Xiang and Zhuang [10] | ARIMA model | Model ARIMA (1,1,1) possessed good prediction effect and can be used as short-term prediction of International crude oil price. |
| Gülen [11] | Cointegertion analysis | Cointegertion analysis was used to confirm the issue of "simple efficiency", which states that the futures price is an unbiased predictor of the spot price, in the case of trading in crude oil futures at NYMEX. |
| Mirmirani and Li [12] | VAR and ANN techniques | This study applies VAR and ANN techniques to make ex-post forecast of U.S. oil price movements, and the analysis suggests that the BPN-GA model noticeably outperforms the VAR model. |
| Lanza et al. [13] | Error Correction model | The comparison of ECM with a naïve (short-run) model suggests that cointegration marginally improves static forecasts in EU. |
| Murat and Tokat [14] | Random Walk | The results showed that (a) both the crack spread futures and the crude oil futures outperformed the RWM; and (b) the crack spread futures are almost as good as the crude oil futures in predicting the movements in spot oil markets. |
| Lin [15] | Grey model | The results show that the model of GM (1,1) is suitable for crude oil prices forecast. |

**Table 2**
Typical literature using the Artificial Intelligence models to forecast crude oil prices.

| Typical literature | Forecasting models | Main results |
|---|---|---|
| Abdullah and Zeng [17] | ANN-Q model | Albeit being a single model prediction, ANN-Q proved to be competitive and comparable to other prediction tools. |
| Kulkarni and Haidar [18] | Multilayer Feedforward Neural Network | On the short-term, futures prices do hold new information on the spot price direction. |
| Movagharnejad et al. [19] | ANN | The method presented in this study is able to promote the forecasting power of the existing oil price prediction models. |
| Shambora and Rossiter [20] | ANN | Superior returns are possible using the network. Overall returns, year-to-year returns, returns over a market cycle, and Sharpe ratios all favor the ANN model by a large factor. |
| Yu et al. [21] | EMD-Based Multiscale Neural Network | The multiscale neural network learning paradigm can effectively improve the generalization capability and be used as a promising tool for crude oil price forecasting problem. |
| Khashman and Nwulu [22] | Support Vector Machines | Experimental results obtained proved that support vector machines could be used with a high degree of accuracy in predicting crude oil price. |
| Li and Ge [23] | Dynamic Correcting Support Vector Regression Machine | The predicting result is very good and can be easily used to predict crude oil price in our life. |
| Xie et al. [24] | SVR | The experiment results show that SVM outperforms ARIMA and BPNN and is a fairly good candidate for the crude oil price prediction. |
| Li et al. [25] | FA-LSSVR | FA-LSSVR outperforms other hybrid and single benchmarks in terms of prediction accuracy, time saving and robustness, suggesting that the proposed approach is a promising alternative to forecast the crude oil price. |
| Chiroma et al. [26] | GA—NN | The proposed GA—NN approach is better than the baseline algorithms in terms of prediction accuracy and computational efficiency and the predicted price and the observed price are statistically equal. |
| Abramson and Finizza [27] | BN | Belief networks have the potential to become important forecasting tools. |

oil forecasting. Inspired by the determination of optimal specification for the VAR model in electricity price forecasting [56], we use the AIC [57] to choose a proper predicting model. In addition, as for the data set splitting for AI forecasting, usually we use convenient ratio such as 7:3,8:2 or 9:1 [16,56,58]. However, there is no efforts taken to investigate how to choose a proper ratio for forecasting. Therefore, we first discuss how to choose the training ratio and lag order according to the character of original data. Then we decompose the data and get the individual components and use AI tool to forecast the price. To be more practical, the future prices are included as supplementary. As for how to evaluate and compare the prediction power of models, we learned from some frequently-used patterns [4,6,59–61].

## 3. Empirical study

To test if the proposed "decompose-ensemble" learning method is effective and superior, we conduct empirical study. In Section 3.1, we describe the details of the empirical study, in Section 3.2 we introduce a whole decompose-ensemble forecasting procedure and in Section 3.3 we thoroughly discuss the comparing results mathematically and statistically.

### 3.1. Experimental design

#### 3.1.1. Data set

In this study, we choose the daily data of West Texas Intermediate crude oil price series. The data can be downloaded in the official website of the US Energy Information Administration (EIA) (http://www.eia.doe.gov/). As for the data range, many researcher chose date series starting from the start of year 2011 to avoid the impact of financial crisis and ignore the public holidays (no official data being reported in those days), which includes 640 observations [4]. The exact time spans are listed in the following Table 3.

In the literature referring to the data set splitting for AI forecasting, the percentage are always above 70%. Usually we use convenient ratio such as 7:3,8:2 or 9:1 [16,56,58]. It is not a waste of time to choose a proper ratio for forecasting. We use the data from year 2011 to discuss this issue. We separately use 4 time series of both spot and future oil price to calculate the performance evaluation criteria (which will be described in details in Section 3.1.2) after ANN training using 5 different training ratio. From the results of the criteria in Table 4, we choose 90% as a proper value for training.

**Table 3**
Selected time spans to forecast crude oil price.

| Starting year | start | end(spot price series) | end(future price series) |
|---|---|---|---|
| 2011 | Jan 03, 2011 | Jul 17, 2013 | Jul 17, 2013 |
| 2012 | Jan 03, 2012 | Jul 17, 2014 | Jul 17, 2014 |
| 2013 | Jan 02, 2013 | Jul 17, 2015 | Jul 17, 2015 |
| 2014 | Jan 02, 2014 | Jul 18, 2016 | Jul 21, 2016 |

#### 3.1.2. Performance evaluation criteria

This part shows the comparing results of different forecasting models from three aspects: level prediction accuracy, directional prediction accuracy and modified Diebold-Mariano (M-DM) test [62]. Based on the Diebold-Mariano (DM) test [63], the test performance of M-DM test is powerful, especially when p-values are computed with a Student-distribution [62,64]. As for the details of the performance evaluation criteria, we can refer to other author's work as follows [4]:

Firstly, two criteria are introduced to measure the level prediction accuracy, i.e. the root mean squared error (RMSE) and the mean absolute percent error (MAPE). The representations are presented as below:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\hat{x}_t - x_t)^2}, \quad (1)$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{x_t - \hat{x}_t}{x_t}\right|, \quad (2)$$

where N is the number of data for testing period, and $x_t$,$\hat{x}_t$respectively denote the real value and estimating value at time t.

Secondly, a useful criterion$D_{st\ at}$ is used to measure the directional prediction accuracy:

**Table 4**
Performance evaluation criteria with different training ratio.

| ratio | Spot price | | | | | Future price | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 2011 | 2012 | 2013 | 2014 | Average | 2011 | 2012 | 2013 | 2014 | Average |
| Dstat | | | | | | | | | | |
| 50% | 0.7656 | 0.4875 | 0.4438 | 0.5531 | 0.5625 | 0.5156 | 0.4375 | 0.5438 | 0.55 | 0.5117 |
| 60% | 0.7617 | 0.5078 | 0.4453 | 0.5586 | 0.5684 | 0.4414 | 0.5156 | 0.5391 | 0.5391 | 0.5088 |
| 70% | 0.7552 | 0.4948 | 0.5781 | 0.5417 | 0.5925 | 0.4531 | 0.5 | 0.4375 | 0.5313 | 0.4805 |
| 80% | 0.7344 | 0.4688 | 0.4531 | 0.4922 | 0.5371 | 0.5234 | 0.4766 | 0.4688 | 0.4844 | 0.4883 |
| 90% | 0.7656 | 0.4688 | 0.5469 | 0.5469 | 0.5821 | 0.4603 | 0.5313 | 0.5625 | 0.4688 | 0.5057 |
| RMSE | | | | | | | | | | |
| 50% | 1.015 | 1.128 | 1.5032 | 1.2903 | 1.2341 | 1.3498 | 1.1202 | 1.9745 | 1.2908 | 1.4338 |
| 60% | 0.9515 | 1.0746 | 1.6494 | 1.3727 | 1.2621 | 1.2414 | 1.0545 | 1.5013 | 1.555 | 1.3381 |
| 70% | 0.9238 | 0.9858 | 1.7073 | 1.2638 | 1.2202 | 1.1599 | 0.9718 | 2.0606 | 1.2208 | 1.3533 |
| 80% | 0.9488 | 0.9654 | 2.1575 | 1.3051 | 1.3442 | 1.1316 | 0.9439 | 1.6867 | 1.3221 | 1.2711 |
| 90% | 1.0536 | 0.8978 | 1.2099 | 1.1425 | 1.0760 | 1.2667 | 0.8616 | 1.2459 | 1.081 | 1.1138 |
| MAPE | | | | | | | | | | |
| 50% | 0.0084 | 0.0088 | 0.0172 | 0.0232 | 0.0144 | 0.0108 | 0.0089 | 0.0235 | 0.0233 | 0.0166 |
| 60% | 0.0079 | 0.0083 | 0.0203 | 0.026 | 0.0156 | 0.0101 | 0.0082 | 0.0188 | 0.0296 | 0.0167 |
| 70% | 0.0077 | 0.0078 | 0.0231 | 0.0258 | 0.0161 | 0.0096 | 0.0077 | 0.0283 | 0.0253 | 0.0177 |
| 80% | 0.0076 | 0.0073 | 0.0336 | 0.0279 | 0.0191 | 0.0093 | 0.0072 | 0.0267 | 0.0277 | 0.0177 |
| 90% | 0.0084 | 0.0065 | 0.016 | 0.0194 | 0.0126 | 0.0105 | 0.0063 | 0.0164 | 0.0188 | 0.0130 |

$$D_{st\ at} = \frac{1}{N}\sum_{t=1}^{N} a_t, \tag{3}$$

where$a_t = 1$when$(x_{t+1} - x_t)(\hat{x}_{t+1} - x_t) \geq 0$, or $a_t = 0$otherwise.

Thirdly, we even use the M-DM test to compare different predicting models and the results show the statistical significance of the models' difference. Since M-DM test is a modified version of DM test, it is easy to realize the basic idea about M-DM test by describing the DM test. In the DM test, the null hypothesis is defined as the S value of tested model is larger than or equal to that of the benchmark model. The DM statistic is:

$$S = \frac{\overline{g}}{\left(\widehat{V}_{\overline{g}}/N\right)^{1/2}}, \tag{4}$$

where$\overline{g} = {}^{1}/_{N}\sum_{t=1}^{N}[(x_t - \hat{x}_{A,t})^2 - (x_t - \hat{x}_{B,t})^2]$, $\widehat{V}_{\overline{g}} = \gamma_0 + 2\sum_{l=1}^{\infty}\gamma_l$, $\gamma_l = \mathrm{cov}(g_t, g_{t+1})$and $\hat{x}_{A,t}$,$\hat{x}_{B,t}$ denote respectively the prediction results of the tested model and benchmark model at time $t$. In M-DM test, modified S value and p-value are reported as the performance evaluation criteria.

#### 3.1.3. Benchmark models

Since we conducted two classes of comparisons to verify the effectiveness and superiority of EEMD methods, this section describes the benchmark models respectively to achieve those two goals.

Firstly, to test the superiority of decompose-ensemble method to normal hybrid one, we compare the EEMD-ANN-ADD model with the CSD-ANN model, in terms of the level, directional predicting criteria and M-DM test statistics. Secondly, to validate the superiority of EEMD to EMD, we compare the counterparts of the EEMD-ANN-ADD model with the EMD-ANN-ADD model.

#### 3.1.4. Parameter settings

In this work, the parameters are set according to the related literature. In EEMD, we set the ensemble number as 100 and the amplitude of added white noise as 0.1 [65]. In the ANN model, we use the neural network toolbox 5.0 of MATLAB package and set the 7 hidden nodes (H), output neuron O as 1, the value of input neurons I equals the lag value of forecasting. All ANN models are training through 10000 times iterations [4].

### 3.2. Decompose-ensemble forecasting model

Overall, four steps are involved in the proposed decompose-ensemble methodology, i.e., model selection, decomposition, individual forecasting and ensemble. All the four steps are presented and the whole process is illustrated in Fig. 1.

For prediction in this work, we implement the direction forecasting strategy. Given a time series$x_t$, the prediction process can be introduced as follows:

$$\hat{x}_{t+m} = f\left(x_t, x_{t-1}, \ldots x_{t-(l-1)}\right), \tag{5}$$

where$\hat{x}_t$denotes the prediction result in period t, $x_t$denotes the actual value and$l$represents the value of lag.

In general, the proposed learning paradigm can be divided into four main steps, i.e., model selection, data decomposition, individual forecasting and ensemble result.

Step1 Model selection using AIC

In order to get good predicting results, we hope to find the most related time series of thee original data to conduct the forecasting. Inspired by the determination of optimal specification for the VAR model in electricity price forecasting [56], we use the AIC [57] to choose a proper predicting model and the process is run by Eviews.

Step2 Data decomposition using EEMD

We use the EEMD to conduct the data decomposition and get several Intrinsic Mode Functions (IMF) and residue.

EMD is developed by Huang [66] and become widely used in signal processing, especially in the decomposition of time series. It has its own advantages for nonlinear data processing such as the self-driven and self-adaptive, but it has the drawbacks of intrinsic mode mixing. To overcome the disadvantage, EEMD is extended from EMD [67]. The EMD and EEMD have widely been used to complex data analysis.

The procedures of EEMD method can be presented as below:

(1) Set the ensemble number and the amplitude of the noise with i = 0.1

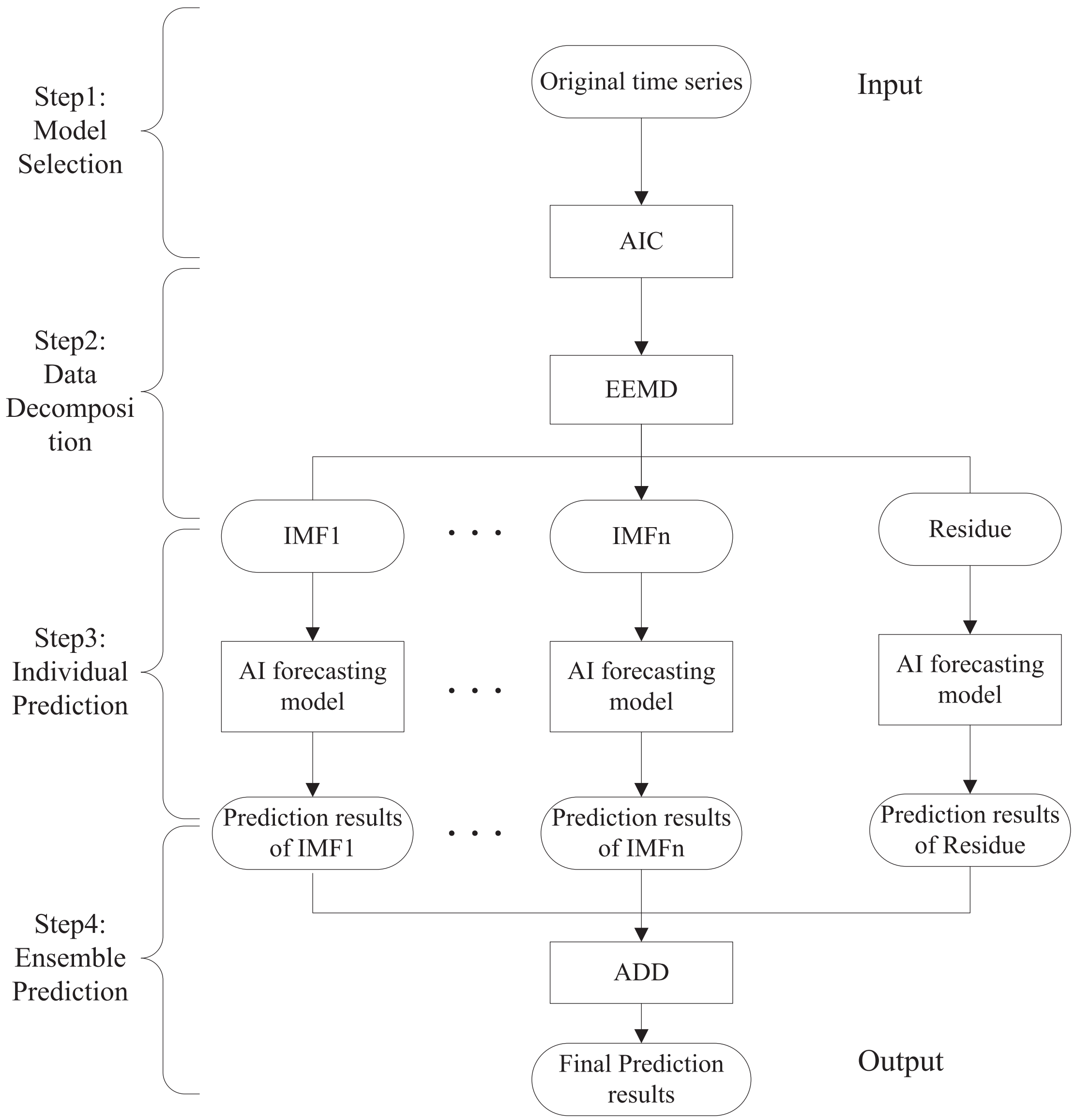


**Fig. 1.** Procedure of the EEMD-based hybrid leaning paradigm.

(2) Add the noise series to the oil price series$X_t$, which could be described as:

$$X_i(t) = X(t) + n_i(t), \tag{6}$$

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

(3) Decompose the crude oil price $X_i(t)$ into IMFs $c_{ij}$ using the classical EMD method.$c_{ij}$denotes the jth IMF of the ith run.
(4) Jump back to step (2) with i = i+1 if i < M, and continue the process with different white noise series in step (2) and (3).
(5) After N runs, count the ensemble mean $c_j(t)$ for every IMF of the decomposition as the eventual results as follows:

$$c_j(t) = \frac{1}{N}\sum_{i=1}^{N} c_{ij}(t), i = 1, 2..., N, j = 1, 2, ..., J, \tag{7}$$

where$c_j(t)$ is the jth IMF component after EEMD part.

Hence, the original crude oil data series can be calculated by adding all the IMFs and one residue:

$$X_t = \sum_{j=1}^{N} c_j(t) + r_N(t), \tag{8}$$

where N is the IMF number, $c_j(t)$ is the jth IMF and $r_N(t)$is the final residue at time t. The EEMD process for international crude oil price is presented in Fig. 2, which presents the spot price series (Jan 03, 2011–Jul 17, 2013), the IMFs and the residue. The horizontal axis represents the 640 data points and the vertical one is for the specific value.

Step3 Individual prediction using ANN

After decomposition, we use a certain powerful AI technique, i.e., ANN, to conduct individual forecasting to every decomposed

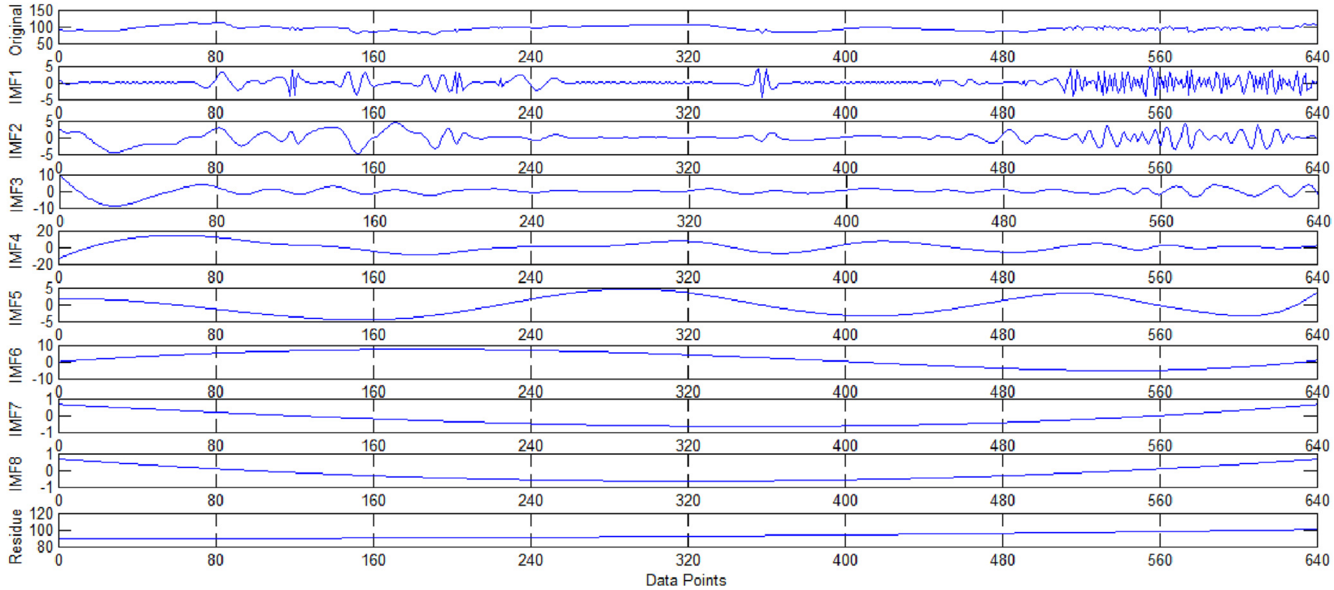

**Fig. 2.** Decomposition components for oil price derived through EEMD.

parts, i.e., IMFs and residue.

ANN is a typical intelligent learning methodology, which is widely used in time series forecasting and has been presented in details in certain article [4]. The output of the ANN forecasting model can be described as:

$$f(x) = a_0 + \sum_{j=1}^{q} w_j \varphi\left(a_j + \sum_{i=1}^{p} w_{ij} x_i\right), \quad (9)$$

where$x_i$ denotes the input patterns, $f(x)$ represented the output, $a_j$denotes the bias of the jth unit, $w_{ij}$ and$w_j$are the connection weights, $\varphi(.)$denotes the transfer function in the hidden layer, p and q respectively represents the number of input and hidden nodes.

In fact, the core idea of FNN is a mapping from the past to the future:

$$x_{t+l} = \phi(x_{t-1}, x_{t-2}, ..., x_{t-p}, W) + \xi_t, \quad (10)$$

where$l$denotes the horizon, $W = w_{ij}$denotes the weight parameter vector and $\varphi(.)$is the training function of FNN.

Step4 Ensemble prediction using ADD

In this step, we add all the predicting results in step 3 together as the ensemble predicting result.

### 3.3. Results and discussion

In this paper, we introduce the “decompose-ensemble” idea to the ANN-based forecasting methods. As for the “decompose-ensemble” method, we use the EEMD method which is based on the EMD method and proposed to overcome the end effects and mode mixing problem of the latter one. In Section 3.3.1, we first validate the “decompose-ensemble” method is better than the normal hybrid one. To explore the superiority of EEMD to EMD, we then compare the predicting results of EEMD-based and EMD-based method. In Section 3.3.2, performance evaluation criteria of different data are presented and used to analyze the robustness of the proposed method.

#### 3.3.1. Experimental results

We compare decompose-ensemble methods and hybrid model in the forecasting methods. As for the performance evaluation criteria, we adopt both directional (in Fig. 3 and RMSE in Fig. 4) and level prediction accuracies (MAPE in Fig. 5). In addition, we take M-DM test to measure the models' difference of forecasting accuracy and the results will be presented in Table 5.

When it comes to the directional prediction accuracies, we refer to Fig. 3, which shows us of different forecasting methods. It is obviously that EEMD-ANN-ADD and EMD-ANN-ADD learning methods achieve high values than the CSD-ANN model. This phenomenon indicates that the “decompose-ensemble” process are better than the normal hybrid model, “decompose-ensemble” does improve the prediction accuracy in the aspect of directional prediction. Also, we find that the EEMD-based one outperforms the EMD-based one, which indicates that it's a good idea to improve the decompose process.

Then we focus on the level prediction accuracies, Figs. 4 and 5 show the comparing RMSE and MAPE results of “decompose-ensemble” methods and corresponding hybrid model. From Figs. 4 and 5, which reflects the results of RMSE and MAPE comparisons, we can obtain that the proposed method in this work, i.e. the


**Fig. 3.** Comparisons of different hybrid ANN methods.

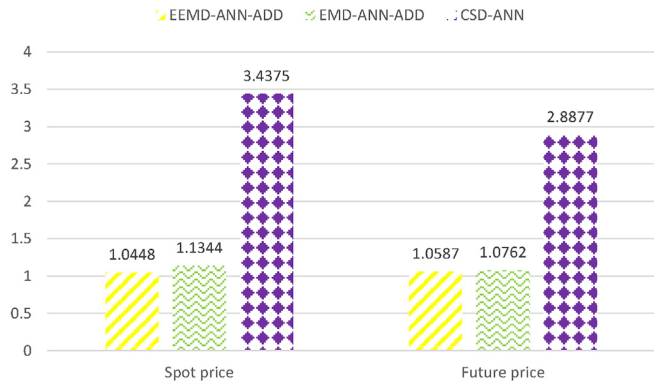


**Fig. 4.** RMSE comparisons of different hybrid ANN methods.

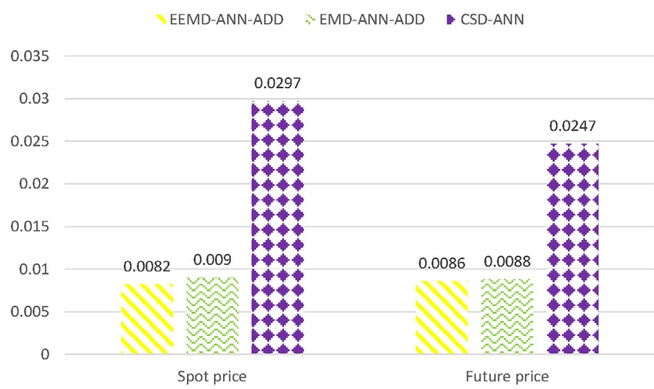


**Fig. 5.** MAPE comparison of various hybrid ANN models.

**Table 5**
M-DM test for different ANN-based forecasting method (data starting from 2011).

| | Tested model | Reference model | |
|---|---|---|---|
| Spot price | | EMD-ANN-ADD | CSD-ANN |
| | EEMD-ANN-ADD | −1.196(0.0000) | −0.633(0.0086) |
| | EMD-ANN-ADD | | −0.175(0.0000) |
| Future price | | EMD-ANN-ADD | CSD-ANN |
| | EEMD-ANN-ADD | −0.401(0.005) | −0.920(0.0000) |
| | EMD-ANN-ADD | | −9.758(0.0000) |

EEMD-ANN-ADD, ranks the best. And EMD-ANN-ADD model ranks the second and performs better than the hybrid model with lower RMSE and MAPE value. In general, Figs. 4 and 5 reflect the efficiency and superiority of EEMD element from the perspective of level prediction accuracies.

To further enhance the statements, we conduct the M-DM tests and get Table 5. In this table, we list the S values and p-values to evaluate the comparing results. When the “decompose-ensemble” models are tested with CSD-ANN model, the p-values are less than 10%.It indicates that “decompose-ensemble” models outperform hybrid model under confidence level of 90%. Moreover, comparing EEMD-ANN-ADD with EMD-ANN-ADD, we find the corresponding p-value is far less than 10%, and the above result show that EEMD-ANN-ADD model is better than EMD-ANN-ADD model under the 90% confidence level, which enhances the evidence of the superiority of EEMD to EMD from the perspective of statistical views.

### 3.3.2. *Robustness analysis*

Usually, we want to know if a model is universe and stable and it could be measured by robustness analysis. In this case, the stability of the forecasting models should also be considered. Based on the pattern of Yu's work [4], which chose the sample data from various time ranges to analyze the robustness, we shift the start point of time period to 2012, 2013,2014 with the same period length.

In the first part, we put the results of all models of EEMD-ANN-ADD, EMD-ANN-ADD and CSD-ANN together and compare their accuracy criteria. The results in Tables 6 and 7 strengthen the conclusion in Section 3.3.1.

### 3.3.3. *Summarization*

From all the above analysis, we can draw the following main conclusions. (1). The proposed decompose-ensemble method obviously outperforms the normal hybrid one in terms of level prediction, direction accuracy and M-DM statistics, which acts as an explanation of the popularity of “divide-and-conquer” philosophy.(2). This novel EEMD-based learning methods are compared with the corresponding EMD-based ones model. Again, the performance evaluation criteria mentioned above certify the superiority of EEMD to EMD. This indicates that EEMD performs better than it original EMD one in data analysis after address the dilemma of intrinsic mode mixing. (3).As for the robust analysis, we use more data (starting from 2012,2013 to 2014) to statistically prove that the conclusion (1) and (2) are not lucky findings. We also compared different models with M-DM test, which significantly agrees with the former two conclusions. (4). The proposed novel EEMD-based method with decompose-ensemble rule is a powerful to predict the oil price from the perspective of prediction accuracy and robustness.

## 4. Concluding remarks

Incorporating the principle of “decompose-ensemble” into the ANN-based methodology, a novel method is developed to predict the international crude oil. Following the philosophy of “divide and conquer” and “hybrid modeling”, we proposed a novel AIC-based decompose-ensemble forecasting framework. Four steps are covered, i.e., model selection via AIC, data decomposition with EEMD, individual forecasting with certain AI method, and finally ensemble forecasting with ADD method for the eventual results. This work has certain novelty: AIC offers reasonable and convincing statement about determining the value of lag. Moreover, we discuss why we choose 90% as training ratio of ANN forecasting. Thirdly, both spot prices and future prices are adopted as original data.

In the empirical study, comparisons indicate that the EMD-based ones are better than the CSD-ANN from the perspective of predicting accuracy and M-DM test statistics. It confirms that decompose-ensemble procedure outperforms the normal hybrid model. Moreover, to validate the superiority of EEMD, we compare the proposed method with EMD-ANN-ADD model. Similarly, we get satisfying results after evaluation. In the robustness analysis part, we use more data to confirm the above statement. The results further confirm that the proposed paradigm is effective and efficient for international crude oil price predicting.

However, there are also some flaws of this method. Initially, the method only take the historical price data as input, but it is well-known that many factors (supply and demand, competition across providers, substitution with other energy forms, technique development, domestic economy, deregulation activities, globalization and even uncertainties caused by political instabilities, wars and conflicts) influence the crude oil price. In addition, the decomposition results rely seriously on the parameter set, but the method fails to provide robust economic theoretical supporting for the decomposing rules. It would be exciting if we could find the mapping relation from certain affecting factors to the IMFs. At last while not the least, this method ignore the impact of public

**Table 6**
Performance evaluation criteria for different ANN-based forecasting method (data starting from 2012,2013.2014).

| | Spot price | | | Future price | | |
|---|---|---|---|---|---|---|
| | EEMD-ANN-ADD | EMD-ANN-ADD | CSD-ANN | EEMD-ANN-ADD | EMD-ANN-ADD | CSD-ANN |
| Starting year: 2012 | | | | | | |
| Dstat | 0.7656 | 0.75 | 0.5469 | 0.7656 | 0.7344 | 0.4844 |
| RMSE | 0.7482 | 0.8091 | 2.3751 | 0.7369 | 0.8128 | 2.9814 |
| MAPE | 0.0054 | 0.006 | 0.0186 | 0.0053 | 0.0059 | 0.0235 |
| Starting year: 2013 | | | | | | |
| Dstat | 0.7813 | 0.7281 | 0.5 | 0.8594 | 0.7188 | 0.4219 |
| RMSE | 0.6635 | 0.8055 | 2.2333 | 0.5661 | 0.6772 | 1.8194 |
| MAPE | 0.0094 | 0.0108 | 0.0324 | 0.008 | 0.0098 | 0.0262 |
| Starting year: 2014 | | | | | | |
| Dstat | 0.8344 | 0.7656 | 0.5 | 0.8281 | 0.7813 | 0.3906 |
| RMSE | 0.9055 | 1.082 | 2.3077 | 0.6186 | 0.7185 | 1.9993 |
| MAPE | 0.0153 | 0.0233 | 0.0409 | 0.0111 | 0.0132 | 0.0354 |

**Table 7**
M-DM test for different ANN-based forecasting method (data starting from 2012,2013.2014).

| | Spot price | | | Future price | | |
|---|---|---|---|---|---|---|
| | Tested model | Reference model | | Tested model | Reference model | |
| Starting year:2012 | | EMD-ANN-ADD | CSD-ANN | | EMD-ANN-ADD | CSD-ANN |
| | EEMD-ANN-ADD | −0.93(0.0039) | −2.059(0.0000) | EEMD-ANN-ADD | −1.581(0.0027) | −2.002(0.0000) |
| | EMD-ANN-ADD | | −0.189(0.0000) | EMD-ANN-ADD | | −1.782(0.0000) |
| Starting year:2013 | | EMD-ANN-ADD | CSD-ANN | | EMD-ANN-ADD | CSD-ANN |
| | EEMD-ANN-ADD | −2.804(0.0000) | −2.075(0.0011) | EEMD-ANN-ADD | −1.631(0.0555) | −8.421(0.0000) |
| | EMD-ANN-ADD | | −8.410(0.0000) | EMD-ANN-ADD | | −10.306(0.0000) |
| Starting year:2014 | | EMD-ANN-ADD | CSD-ANN | | EMD-ANN-ADD | CSD-ANN |
| | EEMD-ANN-ADD | −3.598(0.0000) | −1.743(0.0000) | EEMD-ANN-ADD | −3.678(0.0239) | −4.029(0.0000) |
| | EMD-ANN-ADD | | −3.520(0.0000) | EMD-ANN-ADD | | −10.410(0.0000) |

holidays. This issue includes two aspects: regularly there are two daily blankness every week and irregularly there is no official data reported in other public holidays. Some scholars choose the data after 2010 to ignore the financial crisis's influence. However, it is very hard to take this factors to the forecasting method technically. All the limitations mentioned above is underexplored and meaningful and we will continue exploring them in our future research.

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## Nomenclature

| | |
|---|---|
| AI | artificial intelligence |
| AIC | Akaike's information criterion |
| ANN | artificial neural network |
| CSD | compressed sensing based denoising |
| EMD | empirical mode decomposition |
| EEMD | ensemble empirical mode decomposition |
| FNN | feed-forward neural network |
| IMF | intrinsic mode function |

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