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# A decomposition–integration model with dynamic fuzzy reconstruction for crude oil price prediction and the implications for sustainable development

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ABSTRACT

Grasping the future fluctuation characteristics and trend of oil prices form the basis for a deep understanding of the system mechanisms and development trends of related research fields. However, due to the complex features of the oil price, accurate prediction is very difficult to get. In order to improve the accuracy of international crude oil price predictions, a novel hybrid prediction model is proposed, that is improved on existing decomposition ensemble learning techniques by developing the Dynamic Time Warping Fuzzy Clustering method (FCM-DTW) as a new reconstruction rule. The hybrid model consists of four main steps. First, the West Texas Intermediate (WTI) crude oil spot price is decomposed into a series of relatively stable, different frequency eigenmode components (IMFs) using the adaptive noise complete integration empirical mode decomposition algorithm (CEEMDAN). FCM-DTW is then employed to reconstitute the IMFs into three sub-sequences. Subsequently, an Autoregressive Integrated Moving Average (ARIMA) model is selected according to the data characteristics of the reconstructed sequence and applied to predict the reconstructed components. Finally, a simple additive method is used to integrate the predicted results of each reconstructed component to generate the crude oil price prediction value. The results show that the prediction accuracy of the proposed hybrid model, based on dynamic time warping fuzzy clustering algorithm, is significantly better than the benchmarks considered in this paper.



## 1. Introduction

As a basic energy product, oil accounts for approximately 40% of global energy consumption. As an “industrial blood”, the impact of oil price fluctuations are substantial. For example, the drastic fluctuations in international oil prices have seriously affected the sustainability of economic growth and social development. Wang et al. (2012) established VAR model among oil prices and economic indicators such as economic growth rate, price level, unemployment rate and monetary policy, found that under the price transmission mechanism, oil price volatility imposes significant influences on economic growth rate, price level, unemployment rate and monetary policy. High oil prices encourage the substitution of renewable or clean energy sources for conventional energy sources (Kumar et al., 2012; Managi and Okimoto, 2013). Low oil prices, may against the improvement of environmental pollution since energy restructuring and the development of new energy technology can get retarded (Gallo et al., 2010; Johnson and Crabb, 2007). Dutta (2018) and Ji et al. (2018) also found that the carbon price and clean energy stock market returns are highly sensitive to oil price fluctuations. In order to realize the sustainable development of energy, economy and environment, the development trend of oil price in the future is an essential information that needs to be referred in the process of formulating sustainable development strategy. The Nigeria's finance minister lamented that it is the poor forecasting of oil price and overestimation of oil production that deduced the poor management of annual budgets in Nigeria (Ayadi et al., 2009). Therefore, the purpose of this paper is to build a high-precision prediction model to provide the information of oil price trend for the government to formulate sustainable development strategy.

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Prediction is to analyze the law of its development and change according to the past and present situations of the system or similar system and use this law to predict and describe the state or trend of the system in a certain period in the future. It can overcome blindness and decrease uncertainty when decision makers take actions.

Therefore, crude oil price prediction research has always been a core issue across cleaner production and other relevant sectors of society (Abosedra and Baghestani, 2004). As a research hotspot, the precision of crude oil price prediction models has an important guiding role in the management, control, program development, and risk warning of related fields. The existing literature on crude oil price prediction methods can be divided into two categories: single model and hybrid model methods.

In the research on single model methods utilizing statistical methods, Morana (2001) uses the GARCH characteristics of oil price timing to predict oil prices in the short term. Klein and Walther (2016) uses mixed memory GARCH models to predict oil price fluctuations; Albuquerquemello et al. (2018) uses a Self-Exciting Threshold Auto-regressive (SETAR) model to predict oil prices. Kilian and Lee (2014) uses unrestricted AR, ARMA, and VAR methods to predict crude oil prices and the actual crude oil prices respectively after the year 1973. Lee's results show that the accuracy of the out-of-sample prediction within 12 months is better than that of the classical prediction model, but the prediction accuracy of the classical prediction model is higher for predictions beyond one year. However, the functional forms of traditional econometric models such as X-11-ARIMA, GARCH, AR, ARMA, and VAR are relatively fixed and simplified; the stricter assumptions are applied to the sample data. Although the time series data meeting the assumptions are well fitted to predictive performance, these assumptions are often contrary to the characteristics of real-world oil price time series data: non-stationary, nonlinear, and highly complex.

In the research on single model methods utilizing artificial intelligence methods, the models solve complex predictions by letting machines simulate human intelligence or natural phenomena to obtain more effective and accurate results. Therefore, artificial intelligence technology is prevalent in solutions to predict international crude oil prices. Moosavi et al. (2015) predicts the price of crude oil by neural network model. Qi and Zhang (2009) predicts the daily price of crude oil based on Cluster Support Vector Machine technology. Moshiri and Foroutan (2006) use artificial neural network (ANN) model to predict crude oil prices. Huang and Wang (2018) construct a petroleum price prediction model by using random effects functions and genetic algorithms to improve the ANN. Although a large number of studies have shown that artificial intelligence algorithms can effectively analyze complex systems, artificial intelligence models also have their own limitations, such as parameter sensitivity, local optimization, and over-fitting.

The research on hybrid models has recently emerged as a trend in the field of time series prediction. A hybrid model makes full use of the strengths of different methods to make up for the shortcomings of other methods to improve the analytical performance of the model. By combining the rough set technique with double exponential smoothing model, Haresh et al. (2019) constructed a new hybrid forecasting model and achieved good results in the forecast of tourism demand of air transportation passenger in Australia. Among hybrid models, the hybrid model based on the idea of decomposition–integration is a cutting-edge technology in the study of time series prediction. The main purpose of the decomposition–integration concept is to interpret the generation of time series data from a novel perspective (Zhang et al., 2008). By decomposing a time series into $IMF_s$ based on scale separation, the original tough prediction task were divided into some relatively easy subtasks. This has been explored across a variety of problem domains. Tang et al. (2015) uses a novel CEEMD-based EELM ensemble model to predict the crude oil price. The empirical results show that the model has a good prediction effect. Dang et al. (2013) construct an EMD-based SVM combined model to predict short-term wind speed. The empirical mode decomposition algorithm and a support vector regression algorithm have been used for coal futures price, monthly streamflow at Huaxian hydrological station, complex spectrum sequence, ocean wave height time series data, and China nuclear energy consumption predictions (Zhu et al., 2017; Huang et al., 2014; Duan et al., 2016; Tang et al., 2012). Karthikeyan and Kumar (2013) predicts the monthly rainfall data by constructing an EMD-ARIMA model. The predictive accuracy of the decomposition-based hybrid models is superior to single models in complex data prediction; however, the model is complex and computationally expensive. The model is decomposed into multiple modals and the model encompasses all of the decomposition modalities. Finally, all the data prediction values must be integrated in this established approach.

In order to solve this problem, it is necessary to add the modal reconstruction part in the traditional decomposition–integration model to reduce the model complexity while ensuring the prediction accuracy. Therefore, a model based on the idea of decomposition-reconstruction-integration has also been developed in the field of time series prediction. Wang et al. (2014) reconstruct the decomposition sequence by the run-length decision method to construct an oil price prediction model. The prediction results show that the prediction accuracy of the model is higher than that of the unreconstructed model. Yan et al. (2014) predict the uranium resource price by introducing the mean reconstruction method into the traditional decomposition–integration model. Zhang et al. (2014) use the sample entropy reconstruction decomposition component to predict the wind speed time series data. However, the above research only perform component reconstruction based on static statistical features such as frequency (Wang et al., 2014), average (Yan et al., 2014), complexity (Zhang et al., 2014); the dynamic characteristics of time series data are ignored.

In order to effectively capture the dynamic characteristics hidden in the time series data, this paper introduces a new reconstruction rule - dynamic time warping fuzzy clustering method - to construct a highly accurate decomposition–integration model. By combining fuzzy clustering with dynamic time warping, sample data with great similarities are classified into the same cluster, whereas sample data with great differences are classified into different clusters. In fact, the fuzzy clustering algorithm based on dynamic time warping distance has been widely used in mining data features, and has achieved good results. For example, Hu et al. (2011) use a fuzzy clustering method based on dynamic time warping distance to cluster data samples of similar and spatially related traffic flow data into a group, and found the spatial distribution pattern of road traffic flow, thus providing decision support for the traffic area partition. Wang et al. (2015) improve the prediction model of information particle time series data based on the clustering of information particle data using the clustering algorithm. The dynamic time warping fuzzy clustering algorithm is used to cluster the benchmark datasets from the UCR Time Series Classification Archive (Liu et al., 2018; Izakian et al., 2015). Zhao et al. (2014) combine the dynamic time warping algorithm with the fuzzy clustering algorithm to construct an abnormal point detection model using the real-world energy data from a steel plant.

The main innovation of this paper is to improve the established decomposition and integration prediction model by using a dynamic time warping fuzzy clustering method in order to improve the prediction accuracy of the new model based on the dynamic characteristics of time series data. The structure of this paper is arranged as follows. Section 2 describes in detail the basic theory and algorithms the new decomposition-reconstruction hybrid model uses. Section 3 uses the monthly price of WTI crude oil for empirical analysis. Section 4 summarizes the paper.

## 2. Methodology formulation

### 2.1. Overview of the proposed model

The proposed model is created using four steps (refer to Fig. 1). The process begins using CEEMDAN (refer to Section 2.2) to adaptively decompose the nonlinear, non-stationary and complex crude oil price series into several stationary, different frequency eigenmode components ($IMF_k$) according to the intrinsic characteristics of the data. Next, the IMF sequences are recombined using by dynamic time warping fuzzy clustering (refer to Section 2.3). The statistical characteristics of the reconstructed sequence are further analyzed, and the sequence prediction model is selected according to the test result for prediction (refer to Section 2.4). Finally, the predicted value of the reconstructed sequence is integrated into the final predicted value of the original sequence by simple addition method (refer to Section 2.5).

The model prediction steps are as follows:

Step 1: Perform decomposition on the crude oil price sequence to obtain an eigenmode function and a residual component (CEEMDAN);
Step 2: Recombine the eigenmode component and the residual component by using a dynamic time warping fuzzy clustering algorithm (FCM-DTW);
Step 3: Analyze the statistical characteristics of the above recombination subsequences, and selecting a prediction model according to the test result (ARIMA);
Step 4: Integrate the predicted values of each sequence into the predicted values of the original sequence.

In summary, the final prediction model of this paper is CEEMDAN-FCM-DTW-ARIMA. And these main steps and the related methods are detailed by the following four subsections.

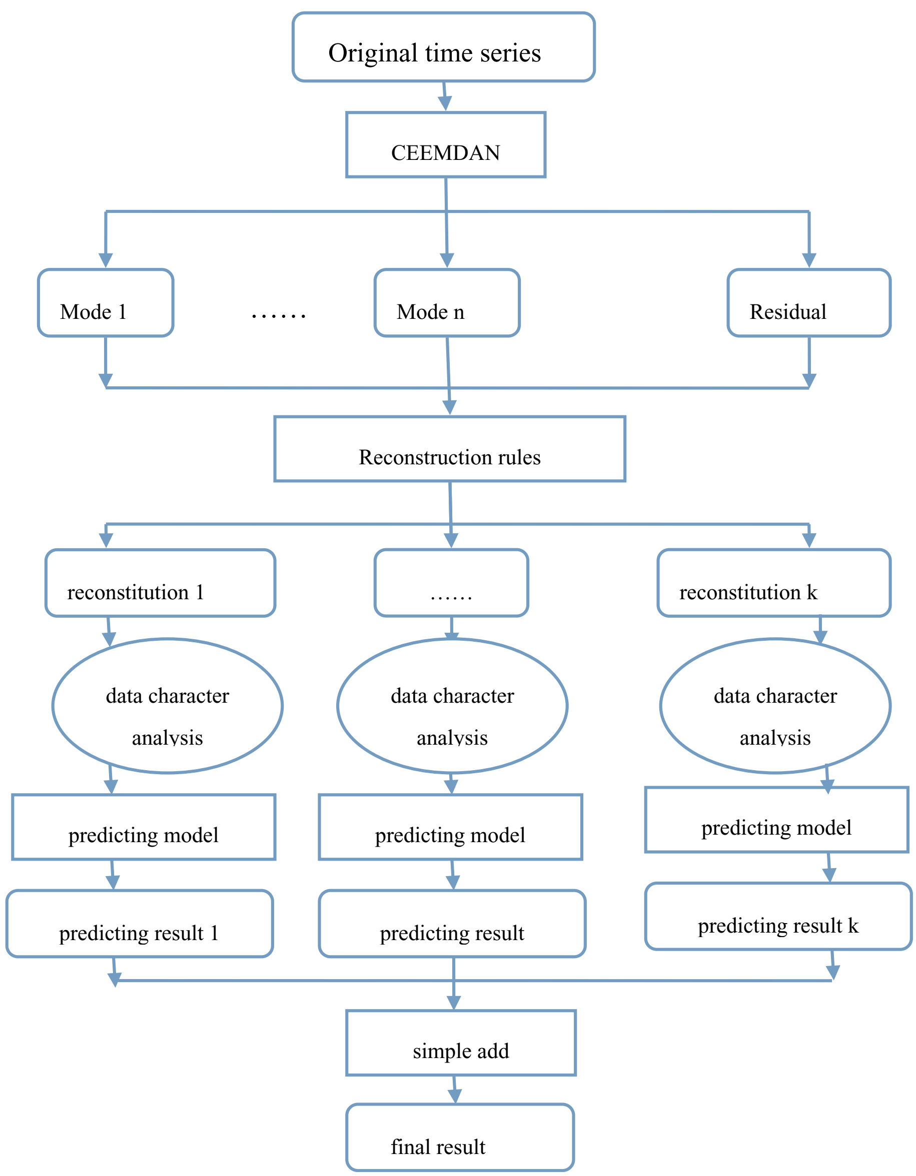


**Fig. 1.** CEEMDAN-Based FCM-DTW model prediction process.

### 2.2. Decomposition step

EMD is a multi-scale analysis method for nonlinear, non-stationary, and complex time series data proposed by Huang et al. (1999). The EEMD algorithm is an improved algorithm obtained by Wu and Huang (2011), which eliminates the EMD modal mixing phenomenon by adding white noise to the original data. However, EEMD cannot maintain the integrity of the EMD and this affects the accuracy of reconstructing the original signal. Therefore, Yeh et al. (2010) propose the CEEMDAN algorithm. The CEEMDAN algorithm performs multiple EMD decompositions; adaptive noise components are added at each stage, and the results are averaged to obtain the IMF. In this way, it maintains the integrity of the EMD decomposition, and solves the problems of the modal mixing phenomenon and the reconstruction error caused by low efficiency. CEEMDAN completely cancels the residual white noise generated by the EEMD algorithm in the decomposition process.

Defined $X(t)$ as the original time series data, and $E_k(.)$ as the $k^{th}$ $IMF_k$ component after the EMD decomposition operation on the original time series sequence. $\omega^i$ is the white noise obeying the standard normal distribution N $(0,1)$, $\varepsilon_k$ is the amplitude coefficient of the white noise added for the $k^{th}$ time. The specific decomposition process of the CEEMDAN algorithm is as follows:

1) White noise is added to the original time series data $X(t)+\varepsilon_0\omega^i(t)$, and EMD decomposition is performed for $I$ times. Then, the results obtained by the $I^{th}$ decomposition are averaged to obtain the first modal component $IMF_1$.

$$IMF_1 = \frac{1}{I}\sum_{i=1}^{I} E_1\left(X(t)+\varepsilon_0\omega^i(t)\right) \tag{1}$$

2) The first residual component is:

$$r_1(t) = X(t) - IMF_1 \tag{2}$$

White noise is added to the first residual component, i.e., $r_1(t)+\varepsilon_1 E_1(\omega^i(t))$, $i=1,2...,I$ and performing EMD decomposition to further obtain the second modal component $IMF_2$.

$$IMF_2 = \frac{1}{I}\sum_{i=1}^{I} E_1\left(r_1(t)+\varepsilon_1 E_1\left(\omega^i(t)\right)\right) \tag{3}$$

Similarly, the $k^{th}$ residual component can be obtained, with $k=1,2...,K$.

$$r_k(t) = r_{k-1}(t) - IMF_k \tag{4}$$

3) White noise is added to the $k^{th}$ residual component, i.e., $r_k(t)+\varepsilon_k E_k(\omega^i(t))$,$i=1,2...,I$, and performing EMD decomposition to further obtain the $k+1^{th}$ modal component $IMF_{k+1}$.

$$IMF_{k+1} = \frac{1}{I}\sum_{i=1}^{I} E_1\left(r_k(t)+\varepsilon_k E_k\left(\omega^i(t)\right)\right) \tag{5}$$

4) Repeat (4), (5) until the residual component is a monotonic function, that is, when the EMD decomposition condition is not satisfied, then the decomposition stops. The resulting residual term is:

$$r(t) = X(t) - \sum_{i=1}^{K} IMF_k \tag{6}$$

$K$ is the number of modal components obtained by the CEEMDAN decomposition process. The relationship between the modal component, the residual term, and the original time series is:

$$x(t) = \sum_{i=1}^{K} IMF_k + r(t) \tag{7}$$

### 2.3. Reconstitution step

#### 2.3.1. Dynamic time warping (DTW) distance

The DTW distance measures the similarity of two time series data by stretching or compressing them. The time series with similar patterns that occur at different time periods are considered to be similar. This method is an effective method to solve the linear drift problem of time series data (Izakian et al., 2015).

The principle of DTW algorithm is as follows: Let the time series $S_1(t)=\{s_1^1,s_2^1,...,s_m^1\}$,$S_2(t)=\{s_1^2,s_2^2,...,s_n^2\}$, where the lengths are respectively $m$ and $n$. Sorting them according to their temporal position, an $m\times n$ matrix $A_{m\times n}$, can be constructed, where each element in the matrix $A_{m\times n}$ is $w_k=(a_{ij})_k a_{ij}=d(s_i^1,s_j^2)=\sqrt{(s_i^1,s_j^2)^2}$. In the matrix $A_{m\times n}$, a set of adjacent matrix elements is grouped into a curved path, denoted as $W=\{w_1,w_2,...,w_k\}$, where is the $k^{th}$ element of $W$, and the path satisfies the following conditions:

(1) $\max\{m,n\}<K\le m+n-1$;
(2) $w_1=a_{11},w_k=a_{mn}$;
(3) For $w_k=a_{ij}$,$w_{k-1}=a_{i'j'}$, satisfying$0\le i-i'$,$0\le j-j'\le 1$, then$DTW(S_1,S_2)=\min\frac{1}{K}\sum_{i=1}^{K}W_i$.

The DTW algorithm can be summarized using the idea of dynamic programming to find an optimal path with the lowest bending cost, i.e.,:

$$D(1,1)=a_{11}, D(i,j)=a_{ij} + \min\{D(i-1,j-1), D(i,j-1), D(i-1,j)\}$$

where $i=2,3,...,m$,$j=2,3,...,n$,$A_{m\times n}$ is the minimum accumulated value of the curved path $D(m,n)$.

#### 2.3.2. Fuzzy k-means clustering

The purpose of cluster analysis is to make the common characteristics of the same type of data as large as possible after the completion of clustering, and the common characteristics among different types of data as small as possible. Among the many clustering algorithms available, there are traditional and fuzzy. Unlike the traditional clustering method with direct partitioning, the fuzzy mean algorithm utilizes the concept of a fuzzy membership degree. The fuzzy mean algorithm obtains the membership degree of each sample point with respect to all cluster centers by optimizing the objective function, thus determining the category of sample points for the purpose of automatically classifying data (Ruspini, 1970).

FCM algorithm adopts the objective function similar to k-means algorithm. The difference between the two is that the objective function of FCM algorithm has an additional term to represent the category weight. The k-means algorithm is relatively simple. It first sets the center point of each partition, so as to form a spherical cluster with the center as the classification basis. In terms of verifying whether the generated partition is reasonable, k-means algorithm takes the sum of distances between points as the measurement criterion. This partition criterion and metric ensure that the algorithm can reach convergence quickly. The algorithm is simple and easy to understand, and can get good clustering results for many clustering problems with low computational cost (Luxburg, 2007). The solution method of FCM is the same as that of k-means algorithm, which inherits the advantages of simplicity and understandability of k-means algorithm.

FCM clusters $N$ time series, $x_1, x_2, \ldots, x_N$ into $c$ information granules—fuzzy clusters. The result of clustering is a set of c cluster centers (prototypes)$v_1, v_2, \ldots, v_c$and a partition matrix $U = [u_{ik}], i = 1, 2, \ldots, c,\ k = 1, 2, \ldots, N$where $u_{ik} \in [0, 1], \sum_{i=1}^{c} u_{ik} = 1 \,\forall k$ and $0 < \sum_{i=1}^{n} u_{ik} < n \,\forall i$. This structure arises through the minimization of objective function:

$$J_0 = \sum_{i=1}^{c} \sum_{k=1}^{N} d^2(v_i, x_k) \tag{8}$$

$$J = \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^m d^2(v_i, x_k) \tag{9}$$

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left( \frac{d(v_i, x_k)}{d(v_j, x_k)} \right)^{2/(m-1)}} \tag{10}$$

where $d$ is a distance function, and $m(m > 1)$is a fuzzification coefficient. $J$ denotes the objective function of FCM. $J_0$ denotes the objective function of k-means algorithm.

The FCM-DTW method integrates the theory from Section 2.3.1 and Section 2.3.2 by considering DTW as a distance function more specifically, the partition matrix is calculated using (10), where $d$ stands for the DTW distance.

## 2.4. Prediction step

### 2.4.1. Auto Regression integrated moving average (ARIMA)

The ARIMA model is a time series analysis method based on stochastic theory proposed by Box and Jenkins (Box and Jenkins, 2010.). It is also called “Box-Jenkins model”. This model has been widely used in predictive analysis in the field of economics. The ARIMA model assumes that the trend of time series fluctuations can be represented by a linear combination of its previous observations in addition to the current and previous random walks:

$$\phi(B)\delta(B)x_t = \theta(B)e_t \tag{11}$$

where $x_t$ is the true value of the time series at time $t$; $e_t$ is the error term, obeying the independent and identical distribution, i.e., $e_t \sim iid(0, \sigma^2)$; $B$ is the lag operator, $\delta(B) = (1-B)^d$ represents the $d$ order difference operation, $\phi(B)$ is the equilibrium reversible $ARMA(p, q)$ autoregressive coefficient polynomial, and $\theta(B)$ is the corresponding moving average coefficient polynomial. The essence of the ARIMA model is the combination of the difference operation and the Auto Regression Moving Average (ARMA) model. This shows that any non-stationary sequence can be ARMA simulated fit to the differential post-sequence as long as it is smoothed by the difference of the appropriate order. Differential operations on the original sequence can be expressed as:

$$\delta(B)x_t = \sum_{i=0}^{d} (-1)^i C_d^i x_{t-i} \tag{12}$$

$$C_i^d = \frac{d!}{i!(d-i)!} \tag{13}$$

That is, the post-differential sequence is equal to the weighted summation of several sequences of the original sequence, which is equivalent to the ARMA model. Because of this weighted summation process, the ARIMA model is called the summation autoregressive moving average model.

### 2.4.2. Threshold auto regressive (TAR)

The TAR model can effectively describe the time series dynamic system of limit point, jumping, dependence, harmonics and other complex phenomena. Due to the control of the threshold, the model has been extensively used: it is robust and the prediction effect of time series is good.

The essence of the TAR model is a segmented Auto Regression (AR) model. The TAR model introduces $l-1$ threshold values within the value range of observation time series $\{x_i\}$ and divides the range into $l$ intervals.

An upper bound and a lower bound can be represented by $r_0$and $r_l$ respectively. According to the number of delayed steps $d$,$\{x_i\}$ is allocated to different threshold regions according to the size of the $\{x_{i-d}\}$ value, and AR models are adopted for $x_i$ within the interval, thus forming a dynamic description of the time series. The model is as follows:

$$x_t = \phi_0^j + \sum_{i=1}^{p_j} \phi_i^j x_{t-i} + \varepsilon_t^j, r_{j-1} < x_{t-d} \le r_j, j = 1, 2, \ldots, l \tag{14}$$

In equation (14), $\varepsilon_t^j$ is a mutually independent sequence of normal white noise, $d$is the number of delayed steps (non-negative integer), $r_j$ is the threshold value, $l$ is the number of the threshold interval, $\phi_i^j$ is the autoregressive coefficient of the$j^{th}$ threshold interval, and $p_j$ is the AR model coefficient of the$j^{th}$ threshold interval.

As the essence of the TAR model is an AR model between partitions, the model test criteria of the parameter estimation method of AR model can be used when modeling. Its modeling essence is a multi-dimensional optimization problem for $d, l, r_j, p_j, \phi_i^j$; genetic algorithms, network searches, and other methods can be used to search for the optimal parameters under the given parameter value range.

The selection of the number of threshold intervals $l$ can be selected theoretically, but in practical applications, a pair is often selected to meet the requirements. Therefore, the number of threshold intervals $l$ is usually set to two. Assuming that the data sample size for training is $n$, the corresponding value of $0.3n, 0.4n, 0.5n, 0.6n, 0.7n$ can be selected successively as the threshold candidate value.

For any gate limit value $r_1$ in the candidate value, the maximum threshold delay is set as $d_{\max}$. For any $1 \le d \le d_{\max}$, the timing data are divided into two categories. For these two sets of data, AR models are established respectively, and the AIC values of the two models are calculated. When the total value of the AIC is the minimum, the corresponding $d, r_1, p_1, p_2, \phi_i^1(i = 0, 2, \ldots p_1), \phi_i^2(i = 0, 2, \ldots p_2)$ parameters are obtained. The formula for calculating the AIC values is as follows:

$$AIC_j = n_j \ln\left(\overline{\sigma_j^2}\right) + 2\left(p_j + 2\right), j = 1, 2 \tag{15}$$

In equation (15), $n_j$ is the number of samples of the $j^{th}$ threshold interval, $\overline{\sigma_j^2}$ is the sample residual variance of the$j^{th}$ threshold interval, and $p_j$ is the corresponding autoregressive model order.

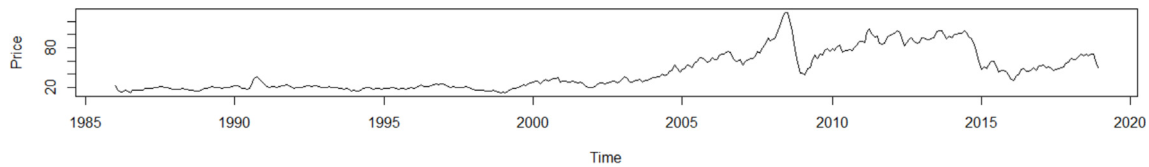


**Fig. 2.** WTI monthly crude oil spot price trend in 1986.1–2018.12 ($/Barrel).

### 2.5. Ensemble step

Simple addition approach is used to obtain the final prediction value, because the original time series data is equal to the sum of the actual values of the derived modes.

$$\widehat{x}_t = \sum_{j=1}^{k} \widehat{x}_{jt} \tag{16}$$

Where, at time $t$, $\widehat{x}_{jt}$denotes the $j^{th}$ forecasting value of reconstruction term, $\widehat{x}_t$is the final prediction value.

## 3. Empirical analysis

### 3.1. Data collection and prediction indicators

This paper selects the monthly data of WTI spot price from January 1986 to December 2018 (data sources from Wind database), a total of 396 data, with the price unit USD/barrel, as shown in Fig. 2. The descriptive statistics for WTI spot price are shown in Table 1 and Fig. 3. The maximum, minimum, and standard deviation indicate the existence of outliers. The sample skewness and kurtosis indicate that the time series have a non-normal distribution.

Stationarity is a key property that should be considered in time series data prediction. The traditional econometric models generally perform well, when the time series data is stationary. The Augmented Dickey-Fuller (ADF) test, whose null hypothesis is nonstationary, is the most popularly used stationary test. As is shown in Table 1, the P value of ADF test is 0.97, which is greater than 0.01, so the oil price data is unstationary.

**Table 1**
Descriptive statistics for WTI spot price.

| | WTI |
|---|---|
| Mean | 43.79 |
| Median | 29.77 |
| Maximum | 133.88 |
| Minimum | 11.35 |
| Standards deviation | 29.49 |
| Skewness | 0.90 |
| Kurtosis | −0.38 |
| ADF test | −1.99 |
| | (0.97) |
| Observations | 396 |

The normalized mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), coefficient of determination ($R^2$) (Poli and Cirillo, 1993) and the Improvement Rate (IR) (Li et al., 2012) are used to measure the prediction accuracy of the model. The calculation formulas of the four evaluation indicators are as follows:

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|x(t) - \widehat{x}(t)\right| \tag{17}$$

The smaller the value of MAE, the better the prediction effect of the model.

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left[x(t) - \widehat{x}(t)\right]^2} \tag{18}$$

The smaller the value of RMSE, the better the prediction effect of the model, which is a widely used predictive evaluation indicator.

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{x(t) - \widehat{x}(t)}{x(t)}\right| \tag{19}$$

MAPE is the average of the sum of absolute values of relative errors. Compared with the simple relative error, MAPE avoids the problem that the positive and negative relative errors cannot be added. At the same time, it also reflects the average level of predicted relative error. It is a numerical predictive evaluation indicator that is widely used, and often has better prediction effect for smaller MAPE value.

$$R^2 = 1 - \frac{\sum_{t=1}^{N}\left[x(t) - \widehat{x}(t)\right]^2}{\sum_{t=1}^{N}\left[x(t) - \overline{x}(t)\right]^2} \tag{20}$$

The coefficient of determination is generally between 0 and 1, and the closer to 1 the value, the better the prediction effect.

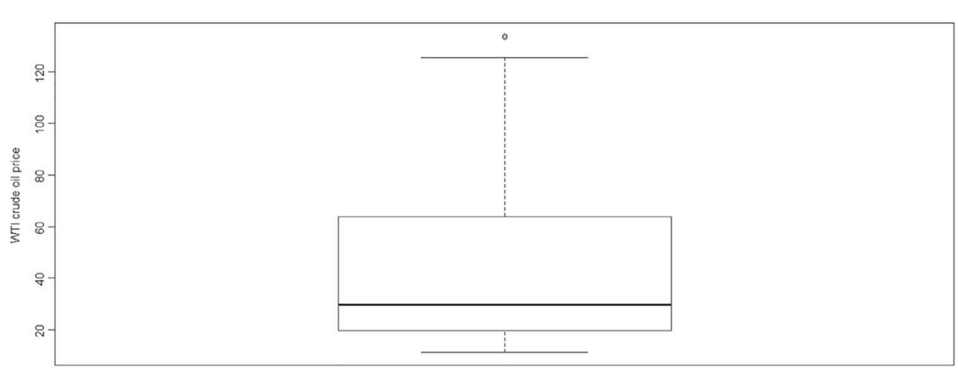


**Fig. 3.** Boxplot for WTI monthly spot price.

$$IR_C = \left|\frac{C_O - C_B}{C_B}\right| * 100\% \tag{21}$$

Where, C denotes the predictive assessment method (MAE, RMSE, MAPE, $R^2$), $IR_C$ denotes the improvement rate of a tested model O over the benchmark B.

### 3.2. Data collection and prediction indicators

From January 1986 to December 2018, the monthly spot price of WTI crude oil are CEEMDAN decomposed, resulting in seven IMF components and one residual component. The decomposition results are shown in Fig. 4.

In this paper, 384 data from January 1986 to December 2017 are

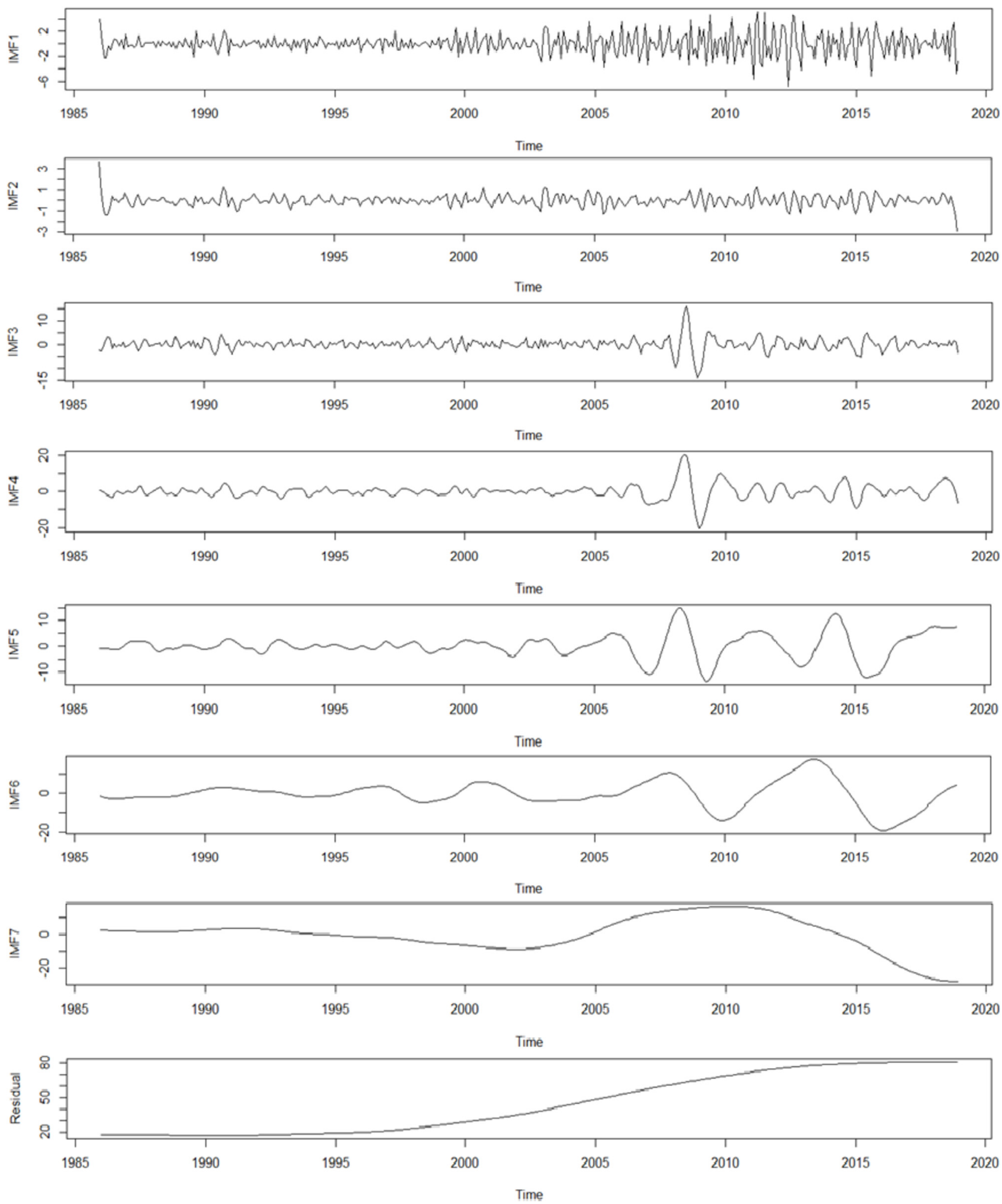


**Fig. 4.** WTI monthly crude oil spot price CEEMDAN decomposition results.

selected as the training set. The data from January 2018 to December 2018 are selected as the test set. The rolling-window methods predict the time series data (Swanson and White, 1995).

The second step of the model is to use the FCM-DTW method for component reconstruction. The fuzzy clustering results for the seven modal components and one residual are shown in Table 2. It can be seen from the table that IMF1, IMF2, and IMF3 belong to the first category with the highest probability, so the three are added as the reconstruction item r1. The probability that IMF4 and IMF5 belong to the second category is the largest, so the two are added as reconstruction item r2. Similarly, the remaining three IMF6, IMF7, and Residual belong to the third category. Therefore, the three items are added up to form the reconstruction item r3. The reconstructed item sequence data chart is shown in Fig. 5.

The variance contribution rate is represented by the ratio of each sequence variance to the original data population variance, i.e., $A_i = \xi_i/\xi$, where $\xi_i$ is the variance of the $i^{th}$ sequence, $\xi$ is the variance of the crude oil price series. The results are shown in Table 3.

The unit root test is used to judge the stationarity of the reconstructed terms. The sample entropy is used to determine the complexity of the reconstructed terms (Li et al., 2006). The inspection structures are shown in Table 4 and Table 5. The descriptive statistics for the reconstructed series are shown in Table 6.

From the above statistical analysis results, it can be known that r1 is a time-series data sequence with stability and relatively high complexity. The variance contribution rate is only about 1.1701%. According to the statistical characteristics of the sequence, the traditional econometric prediction method is used to predict the sequence. r2 is a time-series data with stability and moderate complexity. The variance contribution rate is about 6.1048%. Based on the statistical characteristics of the sequence, the traditional econometric prediction model is employed to predict the sequence. r3 is non-stationary and low-complexity time series data sequence. The variance contribution rate is as high as 88.6261%. Before performing predictive modeling, the r3 sequence needs to be differentially processed to become a stationary sequence. Therefore, the traditional econometric prediction model is used to predict the sequence according to the statistical characteristics of the sequence.

It can be seen that the r3 sequence represents the main long-term trend of oil price series (refer to Fig. 6), which is determined by the level of the world economy. In the short term, due to sudden events, speculative factors and other factors affecting oil prices, oil

**Table 2**
Dynamic fuzzy clustering results.

| | r1 | r2 | r3 |
|---|---|---|---|
| IMF1 | **0.8052** | 0.1638 | 0.0310 |
| IMF2 | **0.8758** | 0.1085 | 0.0157 |
| IMF3 | **0.7158** | 0.2485 | 0.0357 |
| IMF4 | 0.1463 | **0.8230** | 0.0307 |
| IMF5 | 0.0749 | **0.8963** | 0.0288 |
| IMF6 | 0.0057 | 0.0125 | **0.9818** |
| IMF7 | 0.0003 | 0.0004 | **0.9993** |
| Residual | 0.0030 | 0.0044 | **0.9926** |

Note: ri represents the refactoring item i(i = 1,2,3,4).

**Table 3**
Reconstructed component variance contribution rate.

| | r1 | r2 | r3 |
|---|---|---|---|
| variance contribution (%) | 1.1701 | 6.1048 | 88.6261 |

**Table 4**
Stationarity test of reconstructed items.

| | Statistics | P_value | Result |
|---|---|---|---|
| r1 | −11.7487 | 2.2e-16 | Stationary |
| r2 | −2.9834 | 0.00288 | Stationary |
| r3 | −0.8125 | 0.8141 | Non-stationary |
| diff (r3) | −9.1825 | 1.011e-14 | Stationary |

**Table 5**
Reconstruction item complexity test.

| | Sample entropy | Decision (on complexity) |
|---|---|---|
| r1 | 1.2378 | (Relatively) High |
| r2 | 0.5407 | Medium |
| r3 | 0.0423 | Low |

**Table 6**
Descriptive statistics for reconstructed series.

| | r1 | r2 | r3 |
|---|---|---|---|
| Mean | −0.0386 | 0.3236 | 43.5046 |
| Median | −0.0625 | 0.3035 | 28.7518 |
| Maximum | 17.7805 | 34.1895 | 100.4713 |
| Minimum | −16.5662 | −28.3007 | 14.7689 |
| Standards deviation | 3.1905 | 7.2876 | 27.7673 |
| Skewness | 0.1670 | 0.4134 | 0.6883 |
| Kurtosis | 6.2321 | 5.4876 | −1.0316 |

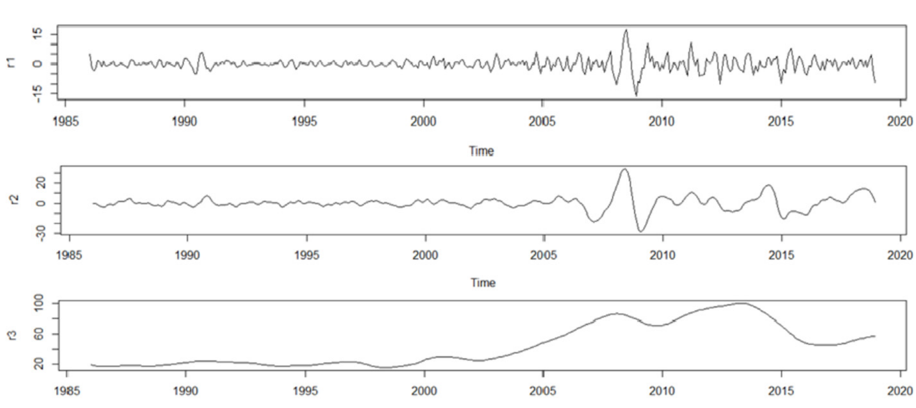


**Fig. 5.** Reconstruction component of WTI monthly crude oil spot price decomposition.

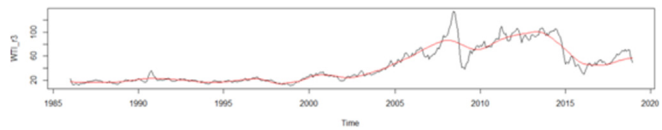


**Fig. 6.** WTI monthly crude oil spot price (black) and reconstruction component r3 (red) ($/Barrel).

prices temporarily deviate from this trend, but as time goes by, the impact of short-term effects of impact factors disappear, making oil prices return to long-term trend levels.

### 3.3. Price prediction and model comparison

By analyzing the statistical characteristics of the reconstructed items and selecting the traditional econometric predicting model to predict the reconstructed items, the representative traditional econometric model for time series prediction is the ARIMA model and TAR model (refer to Section 2.4). The models are used to predict and analyze the reconstructed sequence data respectively. The evaluation results of the model prediction are shown in Table 7. The prediction effect of ARIMA is better than the threshold autoregressive model. Therefore, according to the prediction evaluation index results of the prediction model, this paper chooses ARIMA to predict the reconstruction sequence data.

Finally, the predicted values of each reconstructed item are integrated into the original sequence prediction value. In summary, the prediction model constructed in this paper is CEEMDAN-FCM-DTW-ARIMA (M_0). Its predicted values for the test phase are shown in the red line in Fig. 7. As Fig. 7 shows, the red line is the prediction curve and the black curve at the corresponding position is the real data line. The two lines are close to each other, indicating that the proposed model has a good prediction effect.

In order to test the prediction effect of the model constructed in this paper, with some widely used single model such as ARIMA (M_1), TAR (M_2), the RBF neural network model (M_3) and LSSVM(M_4), and the similar hybrid model CEEMD-Based EELM(M_5) (Tang et al., 2015), prediction results are compared.

For a clear discussion, the prediction results are analyzed from the following two perspectives. First, compare the prediction performances in different predicted time lengths. Second, evaluate the improvement rate of proposed model over the benchmarks via IR.

It can be seen from Fig. 8 that when only consider the RMSE and $R^2$, the proposed model is best for all test periods. For MAE and MAPE, when the prediction period is 3 or 6, the prediction accuracy of the presented model is high. When the prediction period is 12, the MAE and MAPE of proposed model are smaller than those of all single models, but a little bigger than the similar decomposition-ensemble model M_5. Therefore, it can be seen from Fig. 8 that the prediction accuracy of the proposed hybrid model is better than that of the single models. Moreover, when the prediction period is 3 months or 6 months, the proposed model has obvious absolute advantages. As for when the prediction period is extended to 12 months, compared with M_5, the prediction effect of the proposed model needs further analysis.

To further validate the effectiveness of the presented model, the IR, which is calculated based on the data in Table 8, is introduced for analysis (refer to Table 9). Compared to single models, the biggest IR value of MAE,RMSE, MAPE and $R^2$ is 37.5341%, 43.7532%, 39.4555%,572.8278 respectively. These values are sufficient to prove the superiority of the hybrid model. Compared to M_5, the RMSE and $R^2$ of proposed model is increased by 10.0880% and 10.2988% respectively, and the MAE and MAPE is reduced by 9.8306% and 3.3549% respectively. The percentage increase of the predictors of the proposed model is significantly greater than the percentage decrease. In general, the prediction effect of M_0 is better than that of M_5.

The above results demonstrate that the proposed hybrid model is superior to benchmark models for crude oil price prediction.

## 4. Implications for sustainable development

There are two important ways in which oil is related to sustainable development: (a) oil as a source of environmental stress; (b) oil as a principal motor of country's economic growth.

In terms of environment, a country needs to formulate reasonable industrial adjustment policies, petroleum consumption tax, fuel economy standards, etc., to achieve environmental protection and reduce environmental pollution. A precise oil price forecasting model can significantly improve the effectiveness of these actions.

In the national economic operation and growth, for countries with high dependence on oil import, such as China, the price of oil import is determined by the foreign market, which greatly restrains the economic development of oil importing countries. Due to the large demand of oil importing countries, the supply gap will exist for a long time. The need to establish oil reserves is to cope with emergencies, prevent oil supply risks and safeguard national energy security. The improvement of the national oil reserve system needs to consider the future oil price trend, so the proposed model reduces the risk of oil price fluctuation in the process of national oil reserve.

For oil exporters, such as Russia, oil exports are the main source of foreign trade revenue. An excessively low oil price would not only bring about economic collapse, but also bring about political and social collapse. In order to ensure the sustainable development of the country, the future price trend is one of the indicators that must be considered in the policy-making process of oil exporting countries. Therefore, the proposed prediction model can provide reliable information for the policy-making of oil exporting countries.

## 5. Conclusions

The prediction of international crude oil prices remains a

**Table 7**
Accuracy comparison of reconstruction item prediction models.

| | | r1 | r2 | r3 |
|---|---|---|---|---|
| ARIMA | MAE | **2.801429** | **0.521458** | **0.001285** |
| | RMSE | **3.264921** | 0.651953 | **0.001521** |
| | MAPE | **1.324261** | **0.052845** | **2.35E-05** |
| | $R^2$ | **0.19** | 0.971604 | **0.999999** |
| TAR | MAE | 2.995172 | 0.532782 | 0.001851 |
| | RMSE | 3.510275 | **0.619168** | 0.002092 |
| | MAPE | 1.551231 | 0.076731 | 3.41E-05 |
| | $R^2$ | 0.063685 | **0.974388** | 0.999999 |

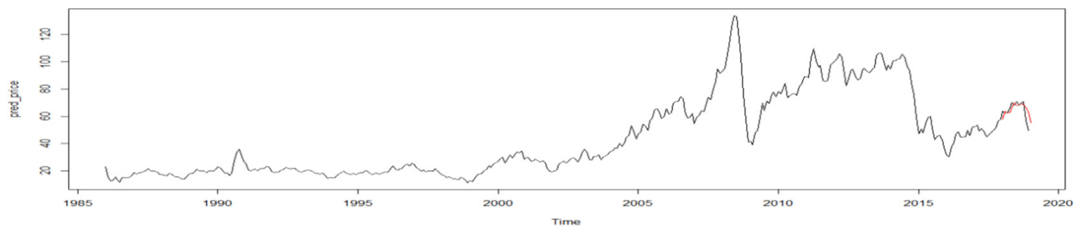


**Fig. 7.** The prediction result of WTI monthly crude oil spot price (red) ($/Barrel).

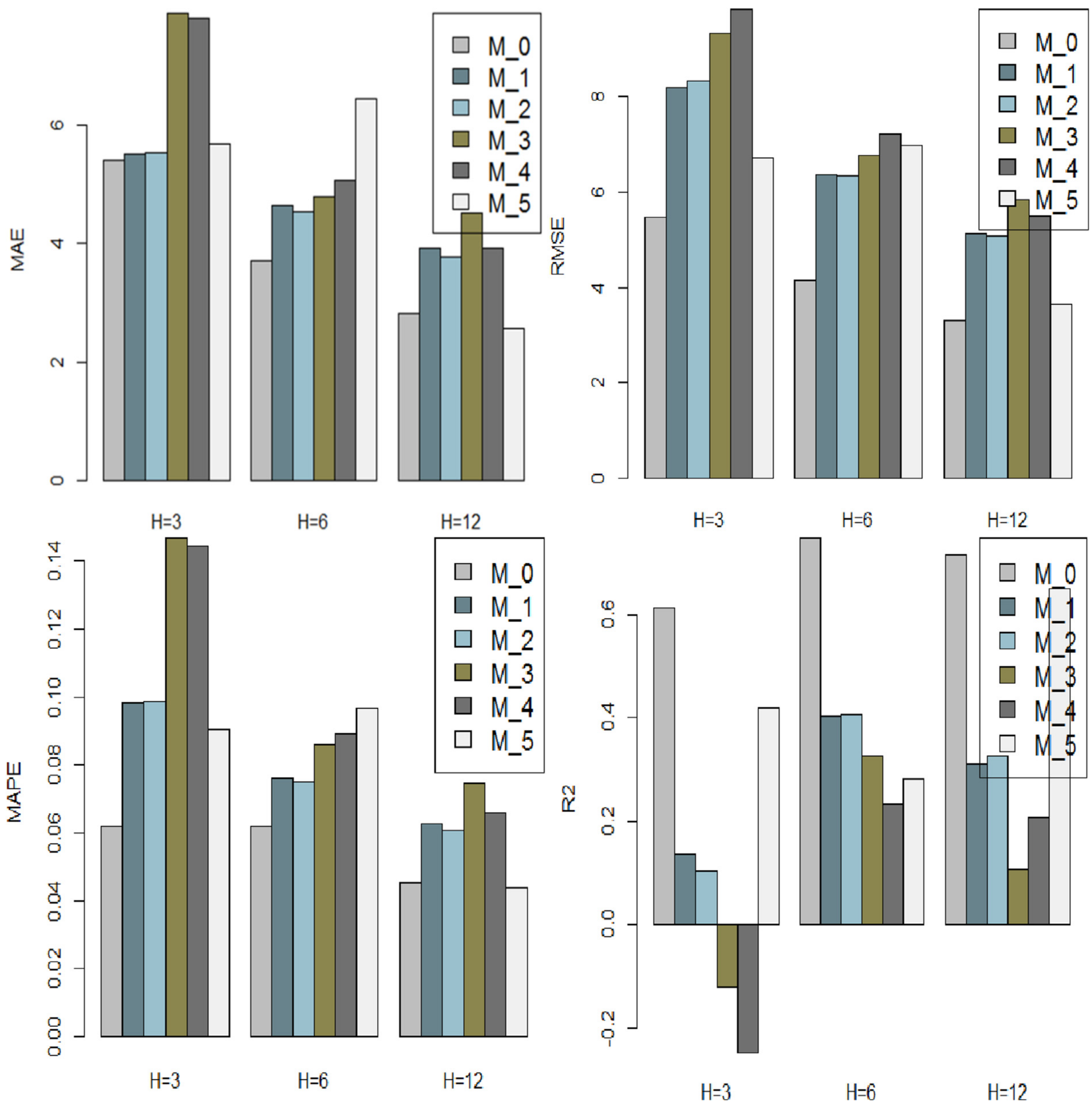


**Fig. 8.** Prediction performances in different predicted time lengths.

research hotspot in the field of predicting. This paper proposes a new hybrid model based on the idea of decomposition–integration to analyze the fluctuation characteristics of oil prices. The proposed method first uses the CEEMDAN decomposition algorithm to decompose the WTI spot price sequences into seven IMF components and a residual component. A new reconstruction rule is introduced – FCM-DTW method - to recombine the component sequences. That is, according to the dynamic characteristics of the decomposition time series data, the similar time series data are divided into the same cluster, and those with larger differences are divided into different clusters. As a result, the seven IMF components and one residual component are reconstructed into three

**Table 8**
Prediction accuracy of different prediction models (H = 12).

| | MAE | RMSE | MAPE | $R^2$ |
|---|---|---|---|---|
| M_0 | 2.8164 | **3.2876** | 0.0452 | **0.7174** |
| M_1 | 3.9338 | 5.1355 | 0.0629 | 0.3103 |
| M_2 | 3.7821 | 5.0704 | 0.0607 | 0.3277 |
| M_3 | 4.5087 | 5.8449 | 0.0746 | 0.1066 |
| M_4 | 3.9292 | 5.5051 | 0.0658 | 0.2075 |
| M_5 | **2.5643** | 3.6564 | **0.0437** | 0.6504 |

**Table 9**
Prediction accuracy improvement rates between M_0 and benchmarks (H = 12).

| Benchmarks | $IR_{MAE}$ (%) | $IR_{RMSE}$ (%) | $IR_{MAPE}$ (%) | $IR_R^2$ (%) |
|---|---|---|---|---|
| M_1 | 28.4061 | 35.9829 | 28.1217 | 131.1596 |
| M_2 | 25.5348 | 35.1616 | 25.5613 | 118.9128 |
| M_3 | 37.5341 | 43.7532 | 39.4555 | 572.8278 |
| M_4 | 28.3219 | 40.2811 | 31.2942 | 245.7459 |
| M_5 | <u>9.8306</u> | 10.0880 | <u>3.3549</u> | 10.2988 |

Note: Underline indicates decreased prediction accuracy.

items with different frequencies and amplitudes, which reduce the complexity of the model while ensuring the integrity of the decomposition effect. Then, by analyzing the statistical characteristics of the reconstructed sequence, the ARIMA model is used to compute the component prediction results. Finally, the component prediction results are directly integrated into the original data prediction value.

In order to illustrate the superiority of the model constructed in this paper, the prediction results are further compared with classical single models (i.e., ARIMA model and RBF neural network model) as well as the CEEMDAN-based EELM hybrid model. The empirical results show that the proposed model is obviously superior.

Compared with the existing prediction models, the hybrid model proposed in this paper has certain advantages: (1) Through CEEMDAN decomposition, the fluctuation characteristics and internal laws of price series at different scales are deeply explored; (2) The new reconstruction rule, dynamic time warping fuzzy clustering method, reconstructs each decomposition sequence, which addresses the dynamic characteristics of time series data, and improves the prediction accuracy of the model.

By using the high-precision prediction model established in this paper, the problem of oil price is deeply studied, the future fluctuation situation of oil price is mastered, and the countermeasures against oil price fluctuation will be formulate accordingly, so as to achieve oil price security. Therefore, the research results of this paper are crucial to national economic growth and sustainable development.

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