

Daily Prediction of Short-Term Trends of Crude Oil Prices Using EMD and Bp Neural Network

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Abstract: The regular swings in the price of crude oil throughout the world may also have an impact on the stability of the global economy and society. Crude oil price fluctuations have nonlinearity, unpredictability, and volatility, which present specific obstacles for forecasting crude oil prices. In this study, we employ a hybrid mannequin to forecast crude oil prices using back propagation neural networks (BPNN) and empirical mode decomposition (EMD). We initially employ the empirical mode decomposition approach to separate the crude oil fees data into a number of unbiased intrinsic mode features (IMFs) and residual sequences in order to increase prediction accuracy (EMD). Additionally, we employed BPNN to forecast the costs associated with WTI and Brent crude oil, respectively. We use inferential and descriptive statistics criteria to the hybrid technique in order to demonstrate the efficacy of the suggested approach. According to the empirical findings, EMD-BPNN has a greater prediction accuracy than existing approaches.

Keywords: BPNN, EMD, IMF's, LSSVR, EMD-LSSVR, Crude Oil data

Date of Submission: 25-08-2022

Date of acceptance: 09-09-2022

I. INTRODUCTION

The raw natural resource known as crude oil is taken from the earth and processed into goods like jet fuel, gasoline, diesel and other petroleum products. Crude oil is one of the most important energy sources used globally. The oil known as "black gold" is responsible for the quick growth of the global oil industry, and a range of financial products made from petroleum are now available on the investment market. [1] The oil market and the economic market have both had an impact on the volatility of oil prices since the supply of oil is essential to the financial development of the majority of industrialized and developing nations. On the other side, the fluctuation in crude oil prices will also add to the macroeconomic turmoil throughout the world. In other words, even a modest bit of oil price volatility will cause the global financial system to experience a butterfly effect, upsetting the balance of global economies. It is feasible that the oil charge, which pervades every area of the national financial system, would seriously impair China's economy's continued and stable expansion. [2] First, accurate crude oil price forecasting may help government officials create additional positive strong insurance plans to a good extent. Second, precise crude oil cost forecasting may also assist companies in minimizing the risk associated with changing oil prices, notably in the mining, petroleum, and transport sectors. Third, all facets of national life are also connected to the forecast of crude oil expenditures. [3] If the price of crude oil can be accurately forecast, residents may prepare ahead and modify their living arrangements to enhance their quality of life. Many research on the forecasting of crude oil prices present a variety of technology techniques. It has been used in econometric models for forecasting oil prices, such as the vector autoregressive (VAR) model, the generalized autoregressive conditional heteroskedasticity (GARCH) models, the autoregressive model (AR), and the *Corresponding Creator (F. Jiang) autoregressive built-in transferring common (ARIMA) model [4]. Aid vector regression (SVR) and artificial neural networks (ANN) are examples of Artificial Genius techniques. [5] Attempting to breakdown the sequence first, then making individual predictions of the subsequent following decomposition, is another method for forecasting crude oil costs. Wavelet evaluation (WT), empirical mode decomposition (EMD), singular spectrum evaluation (SSA), and variational mode decomposition (VMD) are a few examples of decomposition techniques. [6, 7] Using the EMD meta-learning fee model, Zhou et al. [8] predicted a gold rate. To lessen the risk involved with aquaculture, an unique water temperature prediction approach that is fully based on EMD and BPNN is recommended [9]. When compared to the normal simulation results of the hybrid EMD-BPNN model, it has been shown that shooting the non-stationary properties of the water temperature sign after EMD is a very high quality and dependable technique to predict the water temperature in intensive aquaculture.

II. LITERATURE SURVEY

a. Elijah, Olakunle, Tharek Abdul Rahman, Igbafe Orikumhi, Chee Yen Leow, and MHD Nour Hindia. —An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges, IEEE Internet of Things Journal 5, no. 5, 2018, pp.3758-3773.

The surge in global population is compelling a shift toward smart agriculture practices. This coupled with the diminishing natural resources, limited availability of arable land, increase in unpredictable weather conditions makes food security a major concern for most countries. As a result, the use of Internet of Things (IoT) and data analytics (DA) are employed to enhance the operational efficiency and productivity in the agriculture sector. There is a paradigm shift from use of wireless sensor network (WSN) as a major driver of smart agriculture to the use of IoT and DA. The IoT integrates several existing technologies, such as WSN, radio frequency identification, cloud computing, middleware systems, and end-user applications. In this paper, several benefits and challenges of IoT have been identified. We present the IoT ecosystem and how the combination of IoT and DA is enabling smart agriculture. Furthermore, we provide future trends and opportunities which are categorized into technological innovations, application scenarios, business, and marketability.

b. Fukatsu, Tokihiro, Takuji Kiura, and Masayuki Hirafuji, —A web-based sensor network system with distributed data processing approach via web application, Computer Standards & Interfaces 33, no. 6, 2011, pp. 565-573.

We have proposed a Web-based sensor network constructed of Web-based sensor nodes and a remote management system. The Web-based sensor nodes consist of communication units and measurement devices with Web servers. The management system has intelligent processing and rule-based function to manage them flexibly via the Internet and performs various image analyses easily with Web application services. By distributing the image analyses to Web application services, our proposed system provides versatile and scalable data processing. We demonstrated that it can realize the desired image analyses effectively and perform complicated management by changing its operations depending on the results of analysis.

c. Zheng, Lihua, Minzan Li, Caicong Wu, Haijian Ye, Ronghua Ji, Xiaolei Deng, Yanshuang Che, Cheng Fu, and Wei Guo. —Development of a smart mobile farming service system, Mathematical and computer modelling 54, no. 3- 4, 2011, 1194-1203

The Internet of Things (IoT) has tremendous success in health care, smart city, industrial production and so on. Protected agriculture is one of the fields which has broad application prospects of IoT. Protected agriculture is a mode of highly efficient development of modern agriculture that uses artificial techniques to change climatic factors such as temperature, to create environmental conditions suitable for the growth of animals and plants. This review aims to gain insight into the state-of-the-art of IoT applications in protected agriculture and to identify the system structure and key technologies. Therefore, we completed a systematic literature review of IoT research and deployments in protected agriculture over the past 10 years and evaluated the contributions made by different academicians and organizations. Selected references were clustered into three application domains corresponding to plant management, animal farming and food/agricultural product supply traceability. Furthermore, we discussed the challenges along with future research prospects, to help new researchers of this domain understand the current research progress of IoT in protected agriculture and to propose more novel and innovative ideas in the future.

d. N. El-Bendary, E. E. Hariri, A. E. Hassanien and, A. Badr, —Using machine learning techniques for evaluating tomato ripeness, Expert Systems with Applications, vol 42, 2015, pp.1892 -1905

In recent years, a new branch of plant physiology, *plant phenomics*, which focuses on identifying patterns of organization and changes in plant *Phenomes*, i.e., physical and biochemical characteristics, considered as a set of *phenotypes* of a plant organism, has emerged. Phenomics is a postgenomic discipline that actively uses the achievements of the genomic era and bioinformatics. It supplements them with standardized and statistically significant factual material on phenotypes with a high degree of detail. The technique of obtaining and analyzing information about phenotypes in phenomics is called *phenotyping*. *High-performance phenotyping*, providing digital automated analysis of large data samples, has become widespread. Recent progress in high-performance phenotyping has been associated with the development of image registration systems in various spectral regions, approaches to cultivating plant objects

under standardized conditions, sensory technologies, robotics, and methods for data processing and analysis, such as computer vision and machine learning (artificial neural network). Phenomics technologies have a high information content analysis, surpassing human capabilities, performing measurements in the hyperspectral

range using X-ray tomography and ultra- precise “thermal” images, and have a number of other low-invasive and precision approaches. Arrays of data obtained using phenomics technologies are recorded and processed automatically and are free from the problems of subjective assessment and inadequate statistical processing. It is assumed that phenotyping will allow for the creation of digital models of the vital activity processes and the “formation” of plant productivity at the organism level in connection with the dynamics of transcriptomes, proteomes, and metabolomes. Phenomics helps researchers transform a large amount of information received from modern sensors into new knowledge using computer data processing and modeling, reducing the distance from basic science to the practical application of results in crop production and breeding. Phenotyping is actively developing both in laboratory and in green house conditions as well as on open agricultural sites, forests, and in real natural phylogenesis.

III. PROPOSED SYSTEM

In our proposed system we use EMD-BPNN model (empirical mode decomposition and back-propagation neural network model) To predict the price of crude oil.

By "screening" the signal, EMD breaks down the signal into intrinsic mode features (IMF) of extraordinary frequencies. The IMF has the following features: 1) the maximum price and the minimum charge are equal to or unique from the number of zero crossings; and 2) the maximum and minimum envelopes' suggested values must always be zero. Backpropagation is the essence of neural network training. It is the method of fine-tuning the weights of a neural network based on the error rate obtained in the previous epoch (i.e., iteration). Proper tuning of the weights allows you to reduce error rates and make the model reliable by increasing its generalization.

WTI and Brent are chosen as experimental samples in this study for few reasons. WTI, or West Texas Intermediate is a grade of crude oil that is used as one of the several benchmarks in setting oil prices. It is also referred to as Texas light because of its low density and low sulphur content which causes the sweet taste. Brent crude oil is another oil grade used as a benchmark in oil prices all over the world.

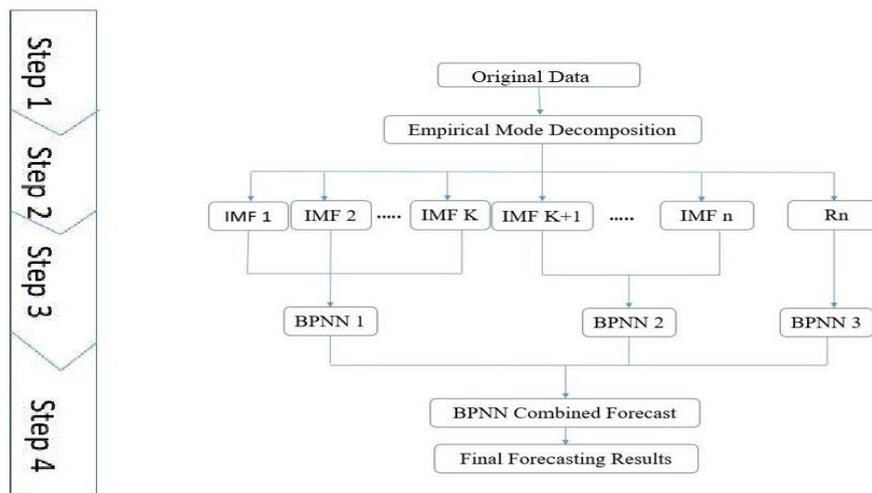


Fig. 1: EMD-BPNN working approach

IMPLEMENTATIONS

crude oil future price prediction

```
In [1]: import numpy as np  
import pandas as pd  
import seaborn as sns  
import matplotlib.pyplot as plt
```

```
In [2]: df = pd.read_csv("oil.csv")
```

```
In [3]: df.head(10)
```

```
Out[3]:
```

	Date	Price
0	May 20, 1987	18.63
1	May 21, 1987	18.45
2	May 22, 1987	18.55
3	May 25, 1987	18.60
4	May 26, 1987	18.63
5	May 27, 1987	18.60
6	May 28, 1987	18.60
7	May 29, 1987	18.58
8	Jun 01, 1987	18.65
9	Jun 02, 1987	18.68

We are importing the required package for the analysis and identifying the crude oil price based on the datasets available from the site Kaggle and the dataset has been imported through pandas library and stored in the variable. Then data has been extracted here we divided the protocol from the entire URL. but need to be divided it separate column

Data Exporting & Cleaning & Data Preprocessing Dropping the unwanted columns and cleaning the data.

```
In [4]: df.isna().sum()
```

```
Out[4]: Date      0
        Price     0
        dtype: int64
```

```
In [5]: # need to convert Date column to standard format
df['Date'] = pd.to_datetime(df['Date'], format="%b %d, %Y")
df.head()
```

```
Out[5]:
```

	Date	Price
0	1987-05-20	18.63
1	1987-05-21	18.45
2	1987-05-22	18.55
3	1987-05-25	18.60
4	1987-05-26	18.63

```
In [6]: # visualizing full data as a line plot
sns.set_style(style='darkgrid')
plt.figure(figsize=(8,5.5))
sns.lineplot(x='Date',y='Price',data = df)
plt.title("brent oil price Trend")
```

IV. RESULTS AND ANALYSIS

Change the format of date and day

```
Out[6]: Text(0.5, 1.0, 'brent oil price Trend')
```

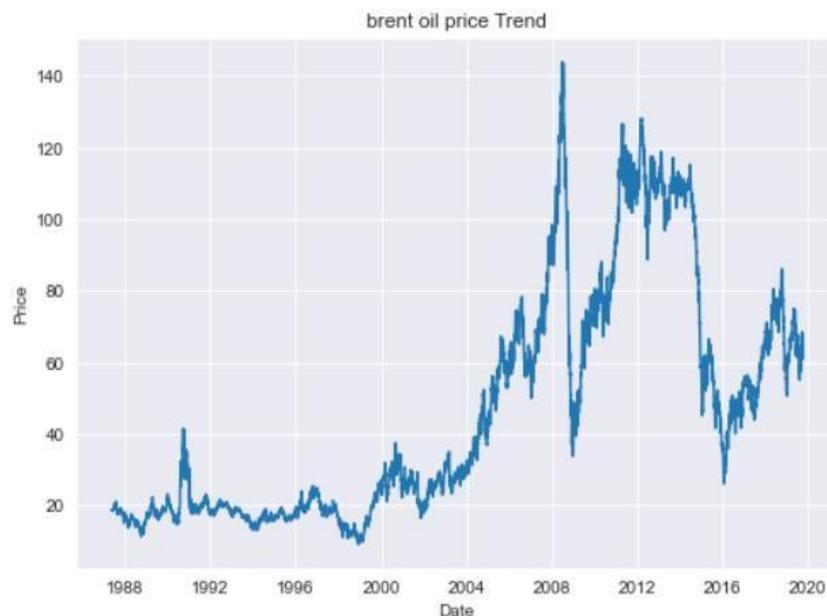


Fig 4.1 Brent Oil Prices

The above figure shows that the Brent Oil Price Trend with year & date for current extraction data.



Fig 4.2 Predicted ratio for Brent Oil data

This function filters the data frame for the specified date range and plots line plot of the data using seaborn.

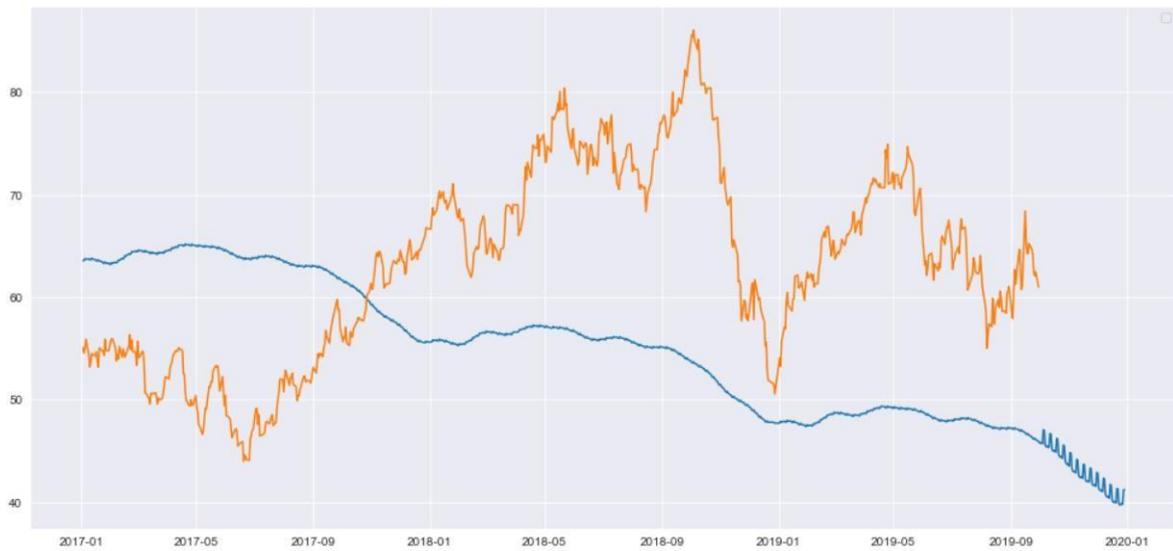


Fig 4.3 Polynomial regression curve for Crude oil

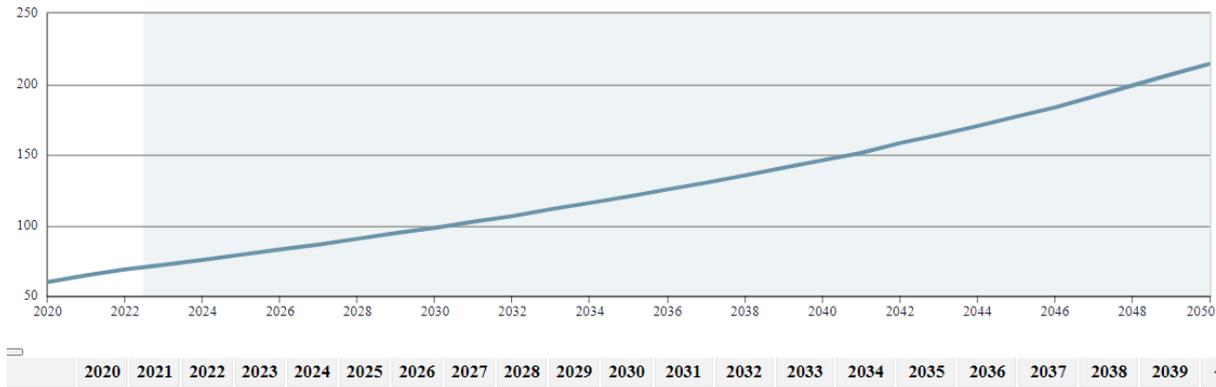


Fig 4.4 prediction of crude oil prices for upcoming years

V. CONCLUSION

Although our forecast models' overall predictions are encouraging, one of its limitations is that they cannot foresee price fluctuations brought on by external variables like conflicts, natural catastrophes, etc. The predicted price may differ from the actual price when one of these factors is present. Additionally, our model forecasts the yearly price of crude oil. In conclusion, our EMD-BPNN model accurately predicts the future price of crude oil as compared with other models. Finally, this model is intended to assist businesses, managers, and the general public in forecasting crude oil prices.

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