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Mid-term forecasting of crude oil prices using the hybrid CEEMDAN and CNN_LSTM deep learning model

Abstract: Forecasting crude oil prices has always been a matter of discussion among energy experts. Due to a significant dependence of the global economy on crude oil, the volatility of the spot price can impact the supply and demand of the market. Moreover, crude oil is still the primary energy for transportation worldwide. Although renewable energy sources have developed significantly, crude oil has been dominant in transportation fuels in the last few decades. This study focuses on mid-term multi-step forecasting and provides a forecasting model that provides a robust prediction for 60 to 90 steps ahead. Our main objective is to develop a forecasting model that can maintain high accuracy and low errors. Our analysis uses a hybrid Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and the Convolutional Neural Network, Long Short-Term Memory (CNN_LSTM) deep learning model. These three techniques, which have different advantages, are put together, and the combination of them is able to identify features (trend and seasonality) in historical data learning and perform high prediction accuracy for next-term prediction. We compared the proposed model with other decomposition and deep learning techniques. The proposed model shows lower Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values than other benchmark models for Brent and crude West Texas Intermediate (WTI) oil prices – the proposed model's Mean Absolute Percentage Error (MAPE) results in better forecasting with MAPE values between 4 to 10. The simulation with box plot analysis also gives

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a quartile range value below 0.2, which shows the stability of the model in each iteration. Finally, the proposed model can provide a robust forecasting model for multi-step mid-term forecasting.

Keywords: forecasting, crude oil price, complete ensemble empirical mode decomposition with adaptive noise, convolutional neural network, long short-term memory

Introduction

Crude oil continues to be a vital energy source, powering most of the transportation fuel activities in all countries of the world. Although the development of other resources continues, crude oil still accounts for around 91% of the world's energy consumption in transport in 2022 (Fig. 1). Therefore, rising oil spot prices should be monitored by various groups, such as government, economists, and businesspeople, because the impact may lead to higher transportation and delivery costs. This impact makes crude oil price forecasting studies very important and provides an early warning system for making business transportation and delivery plans. In addition, it meets the need of economists to estimate how essential processes and events, such as, e.g., wars, natural disasters, or infectious disease outbreaks, can impact the value of crude oil prices and also predict how long the impact will occur (Zhang et al. 2022).

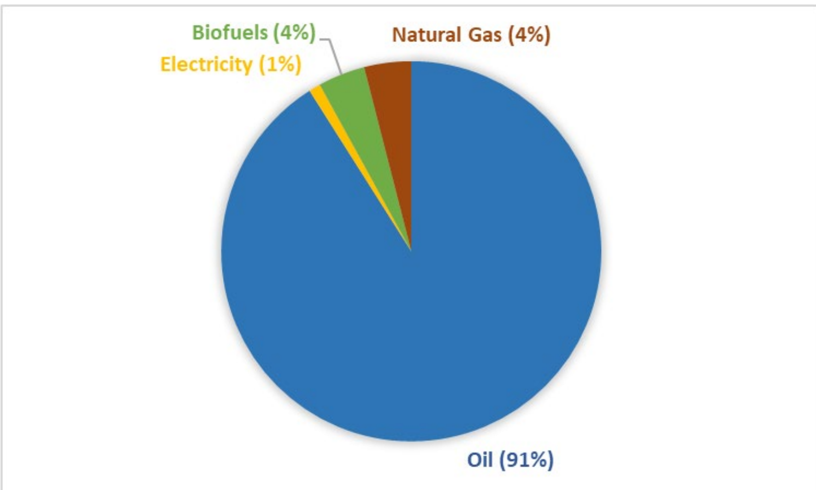

Fig. 1. World energy consumption in transport fuel 2022 (Energy for Transportation 2023)

Rys. 1. Światowe zużycie energii w transporcie paliwowym 2022

Some forecasting research articles use short-term (<2 months) forecasts for model forecast periods (Ghalayini 2017; Tissaoui et al. 2023), which are less helpful than long-term forecasts in interpreting oil forecast observations. Crude oil forecasting requires longer-term forecasting, three to four months ahead, so that observers and economists can further analyze oil price movements and issue analyses and policies as soon as possible before the negative potential is exacerbated. Longer-term forecasting often leads to increased measurement error, as some forecasting models may provide low values in the short term but fail to maintain them in the medium term, reducing observers' confidence in the model and making the forecasting model less useful. Economic and business analysts need a medium-term forecast to predict the long-term stability of the price of crude oil. If there is a severe unexpected event in the world today, the effect can be reliably predicted with the scope of the medium-term forecast. Therefore, in this study, we try to use a hybrid forecasting model with a combination of Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and deep learning model, Convolutional Neural Network – Long Short Term Memory (CNN-LSTM), to build a forecasting model that provides high accuracy for the medium-term period (Lazzeri 2020). For comparison, we also perform calculations for other decomposition models such as Empirical Mode Decomposition (EMD) and non-decomposition and deep learning models such as Artificial Neural Networks (ANN), Single CNN, and LSTM. In addition, this paper presents multi-step forecasts, especially for the medium term, so that the stability error values at each step and trend will be illustrated in graphs.

The use of deep learning models is the latest breakthrough in quantitative data analysis, with some popular applications including forecasting techniques, language modeling, image recognition, text analysis, and data labeling (binary and multi-class classification). Deep learning has non-linear factors of the activation function, which is one of the advantages of ordinary statistical forecasting models such as ARIMA or exponential smoothing.

Some papers related to crude oil prices with deep learning, for example, Yu et al. (2008) used neural network (NN) technique with EMD decomposition for Brent oil prices, and Bao et al. (2011) used LSSVM machine learning combined with wavelet decomposition for two types of datasets (daily Brent and WTI crude oil prices). In addition, Xiong et al. (2013) used weekly crude WTI data with EMD and feedforward neural network (FNN) approaches. The evolution of FNN, namely Artificial Neural Network (ANN), with the addition of a back-propagation mechanism, was also introduced by Abdel-Khalek et al. (2019) for the case of energy border transmission. The latest deep learning model, namely LSTM, was also used by Lu et al. (2021) for crude oil prices by comparing it with six different forecasting models, including ARMA, Random Walk, and Elman Neural Network, and it seems that LSTM gives the lowest error value. Most forecasters continue to develop this deep learning method for forecasting applications, and one of the hot topics is crude oil prices. Among some of the above deep learning models that have been proven to give satisfactory results compared to other models, in this paper, we will use a hybrid deep learning model, namely CNN-LSTM. As a comparison, we will use other deep learning models.

Predictive models can provide more satisfactory results when combined with appropriate decomposition methods, where some popular decompositions are Empirical Mode Decomposition (EMD), Complete Ensemble EMD, Wavelet Decomposition, or Hodrick-Prescott (HP) Filter. This decomposition process can split the original data into several data sets that are easier

Table 1. Studies related to crude oil price and deep learning forecasting

Tabela 1. Badania dotyczące prognozowania cen ropy naftowej i głębokiego uczenia się

References	Data	Methods	Results
Yu et al. (2008)	Crude oil WTI Price	Sparse Representation (SR) and Feedforward Neural Network (FNN)	The SR-FNN shows better accuracy than single FNN and Wavelet Decomposition (WD) and FNN
Ramyar and Kianfar (2019)	Crude oil Brent and WTI Price	Multi-Layer Perceptron (MLP)	MLP model outperforms Vector Autoregression (VAR)
Abdollahi (2020)	Crude Oil WTI Price	Complete Ensemble Empirical Mode Decomposition (CEEMD), Support Vector Machine (SVM) and Markov Switching GARCH	The proposed model performs better than without decomposition
Saghi and Rezaee (2023)	Crude Oil WTI Price	Wavelet Decomposition and MLP	The proposed model more accurate than other benchmark models
Lu et al. (2021)	Crude oil Brent and WTI Price	Long short-term Memory (LSTM)	LSTM performs better than different techniques, such as Random Walk (RW), ARMA, Elman Neural Network (ENN)
T. Zhang et al. (2021)	Crude oil Brent and WTI Price	Ensemble Empirical Mode Decomposition (CEEMD), Extreme Learning Machine (ELM) with Particle Swarm Optimization (PSO)	The model significantly improves prediction accuracy

to analyze by the forecast model than the previous data; reuniting the data is also quite simple, only the addition process. The Hodrick-Prescott (HP) filter is one of the well-known decomposition functions. This technique is also a trend extraction used by Ouahilal et al. (2017) to optimize the support vector regression (SVR) algorithm for the stock market price case. Qunli et al. (2009) and Shabri and Samsudin (2014) used the wavelet decomposition technique for WTI and Brent crude oil prices. From several article descriptions published in Table 1, decomposition methods are generally the latest hybrid method that can increase prediction accuracy compared to non-decomposition models. From several existing decomposition techniques, this paper will use CEEMDAN, which is the development of EMD techniques with reduced mode mixing techniques. Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) solves EMD's weaknesses by reducing some useless Intrinsic Mode Function (IMF) and computational costs. In addition, CEEMDAN can solve the problem of white noise elimination from EEMD residuals. This CEEMDAN technique has been used in other cases, such as ozone concentration (Cheng et al. 2021) and carbon emission (Yun et al. 2023). Yun et al. (2023) used this CEEMDAN decomposition in combination with deep learning LSTM and showed more accurate results.

Here, the presented hybrid forecasting stage is a combination of three things, which, to our knowledge, has never been done in other crude oil price forecasting articles, namely [1] using CEEMDAN decomposition on the dataset of Brent and WTI crude oil prices at the beginning of the process, [2] using a combination of Convolutional Neural Network [CNN] and LSTM as a forecasting model, and [3] performing multi-step forecasting with an emphasis on medium-term forecasting, i.e. between 60 and 90 days of step. This study aims to compare the accuracy of the CEEMDAN_CNN-LSTM model with other decomposition and deep learning models. In addition, this paper provides an overview of the CEEMDAN development techniques and discusses how the CNN-LSTM model is used in forecasting applications.

The rest of the paper is structured as follows: Section 1 describes the theory of CEEMDAN decomposition, CNN, and LSTM. Section 2 contains statistical descriptions of the data, visual plots, and the mechanism by which the forecasting model is applied. Section 3 contains an analysis of the model's measurement error value by comparison with other models. Section 3 shows how the proposed model can maintain the decline in accuracy in the medium-term forecast. Finally, the last part is the conclusion.

1. Previous studies

1.1. Time series forecasting

Time series forecasting of 1-dimensional historical data $\{x_1, x_2, ..., x_T\}$ in $t = 1,2,...,T$ predicts the next value with a linear or non-linear relationship. For n-step forecasting, we obtain the prediction of n numbers: $\hat{x}_{T+i|T}$, where $i = 1,2,3,...,n$. The forecasting model identifies $\hat{x}_t$ with the expectation of a minimum estimation error, $e_t = x_t - \hat{x}_t$, where e_t = error prediction.

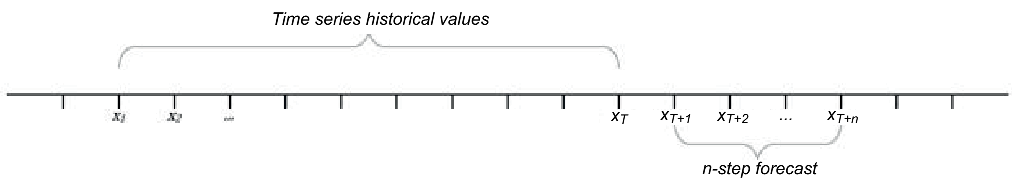

Fig. 2. N-step forecasting illustration

Rys. 2. Ilustracja prognozowania n-etapowego

1.2. CEEMDAN decomposition

CEEMDAN was introduced by Torres et al. (2011) to improve the EMD model previously introduced by Huang et al. (1996). EMD has a mode-mixing problem that gives two negative conditions that arise, namely [1] when one intrinsic mode function (*imf*) has a significant difference in scale because it is difficult to separate it into two or more *imfs*, and [2] a situation where the IMF has data similar to the original data, resulting in an unsuccessful decomposition process. Wu and Huang (2009) also introduced a solution to the development of EEMD with the addition of white noise so that

$$x_i(t) = x(t) + \beta\omega^{(i)}(t) \tag{1}$$

where:

$x(t)$ – a time series dataset,
$x_i(t)$ – EEMD generated of a dataset,
β – standard deviation of white noise,
$\omega^{(i)}(t)$ – white noise $\sim N(0,1)$.

The $x_i(t)$ keeps generated until satisfying zero crossings, and extrema differ at most by one, and we get imf_i candidate or $d_i(t)$.

Torres et al. (2011) recommend CEEMDAN by modifying the generated EEMD process, which has the disadvantage of having to perform the generated EEMD ($x_i(t)$) repeatedly so that the CEEMDAN calculation provides a more straightforward *imf* generation and can reduce the computation time. Let the notation imf_i in CEEMDAN be denoted as $\tilde{d}_i(t)$, and for different i, there is a different process

a) For $i = 1$, the process is similar to the EEMD process

$$\tilde{d}_1(t) = \frac{1}{N}\sum_{i=1}^{N} d_1^i(t) = \frac{1}{N}\sum_{i=1}^{N} E\left(x(t) + \beta_0\omega^{(i)}(t)\right) \tag{2}$$

where:

$E(\cdot)$ – generating EMD decomposition,
N – the number of generating EEMD to reach candidate *imf*. Residual formula is

$$r_1(t) = x(t) - \tilde{d}_1(t) \tag{3}$$

b) For $i = 2$,

$$\tilde{d}_2(t) = \frac{1}{N}\sum_{i=1}^{N} d_2^i(t) = \frac{1}{N}\sum_{i=1}^{N} E_1\left(r_1(t) + \beta_1 E_1\left(\omega^{(i)}(t)\right)\right) \tag{4}$$

$$r_2(t) = r_1(t) - \tilde{d}_2(t) = x(t) - \tilde{d}_1(t) - \tilde{d}_2(t) \tag{5}$$

c) For $i > 2$,

$$\tilde{d}_i(t) = \frac{1}{N}\sum_{i=1}^{N} d_{i-1}^{i}(t) = \frac{1}{N}\sum_{i=1}^{N} E_1\left(r_{i-1}(t) + \beta_{i-1}E_{i-1}\left(\omega^{(i)}(t)\right)\right) \tag{6}$$

$$r_i(t) = r_{i-1}(t) - \tilde{d}_i(t) \tag{7}$$

The coefficients β_i can be defined as the chosen standard deviation for the added white noise of each stage i. This value is expected to be small so that it does not change too much from the original data set value $x(t)$. Looking at Eq. (6) above, the adaptive noise formula is $\beta_{i-1}E_{i-1}\left(\omega^{(i)}(t)\right)$, which is performed continuously from $i = 1$ to N. In other words, at each stage i, $\tilde{d}_i(t)$ will always depend on the previous one.

The final residual is

$$R(t) = x(t) - \sum_{k=1}^{K} \tilde{d}_k(t) \tag{8}$$

where

k – numbers of *imfs*, or we can have decomposition formula as

$$x(t) = \sum_{k=1}^{K} \tilde{d}_k(t) + R(t) \tag{9}$$

1.3. Convolutional Neural Network (CNN)

The Convolutional Neural Network is a neural network technique that convolves and combines n-dimensional quantitative data according to the filter's dimensions. CNN was developed by Fukushima (1980), who was inspired by Hubel and Wiesel (1959) while studying the visual techniques of cats in response to the smallest part of their visual neurons. In other words, this technique reduces the number of input data sets with several techniques without reducing the accuracy obtained and even gives the convolved data results an advantage in interpreting the correlation of complex data sets. With a large amount of input data (x_t) to the neural network, the training process involving weight $\{w_i\}$ and bias $\{\theta_i\}$ will require considerable computation time. It will increase when we add hidden nodes to it. Therefore, several techniques in CNN, such as filtering, pooling, padding, shredding, and flattening, can reduce the number of input nodes before entering the next model, such as ANN or LSTM. This CNN technique is often used in image classification with hundreds of input pixels.

For forecasting models, we use 1-dimensional CNN; this technique has the advantage [1] of reducing the input data to the following model (e.g., LSTM). As seen in the kernel filter technique in Figure 3, the time series data $\{x_t\}$ decreases with the kernel dimension ($n \cdot 1$). [2]

identifies any small shifts in the input data set. In Figure 3, it can be seen that the kernel attempts to combine each of the n inputs with multiplication and addition operations into one value at the output x_t'; this can identify the features of each n-sequence in the left, middle, or right part of the dataset.

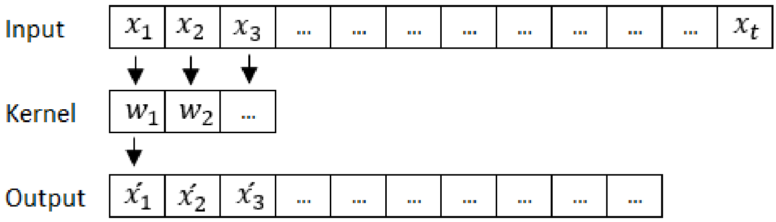

Fig. 3. One-dimensional CNN

Rys. 3. Jednowymiarowa sieć CNN

In the CNN, there is an optimization process to improve the results of the iterations; therefore, CNN is one of the deep learning categories. The concept of learning is inseparable from the CNN stage, and the most popular concept is the Adamax optimizer. Adamax is an optimizer that combines learning rate and gradient (Kingma and Ba 2015) with the following formulation

$$w_{t+1}^{new} = w_t^{old} - \frac{\eta}{S_t} \cdot \hat{V}_t \tag{10}$$

$$\hat{V}_t = \frac{V_t}{1-\beta_1^t} \tag{11}$$

$$V_t = \beta_1 V_{t\ 1} + (\ -\beta_1)\left(\frac{\partial}{\partial}\right) \tag{12}$$

$$S_t = max\left(\beta_1 S_{t-1}, \left|\frac{\partial \mathcal{L}}{\partial w_t}\right|\right) \tag{13}$$

where:

η – the learning rate,

$\frac{\partial \mathcal{L}}{\partial w_t}$ – the gradient function,

$\mathcal{L}$ – the loss function.

Adamax uses the concept of momentum (V_t) and β.= momentum rate.

1.4. Long-Short Term Memory (LSTM)

In the case of image recognition, CNN is usually combined with ANN, while in the case of prediction, CNN is more appropriately paired with LSTM. LSTM is the evolution of ANN with the concept of pattern recognition, previously present in the Recurrent Neural Network model, refined into LSTM. LSTM was developed by Hochreiter and Schmidhuber (1997). RNN has the ability to recognize a sequence of data per element by predicting what value should come after it. This concept is widely used in text generation and machine translation, where the input data is limited. However, for predicting training data that is very large and complicated, RNN has problems called exploding gradient and vanishing gradient. These two problems mean that gradient descent cannot provide a significant optimizer for the model. Therefore, the LSTM model provides a solution.

LSTM (Fig. 4) has three main gates: the forget gate, the input gate, and the output gate, where the input and output gates have right and left parts. LSTM has a characteristic long-term memory line (line at the top) where the previous data can influence the output value in the new data, hence the name long-term line. Meanwhile, the short-term line (bottom line) influences the current data x_t and the previous data x_{t-1}.

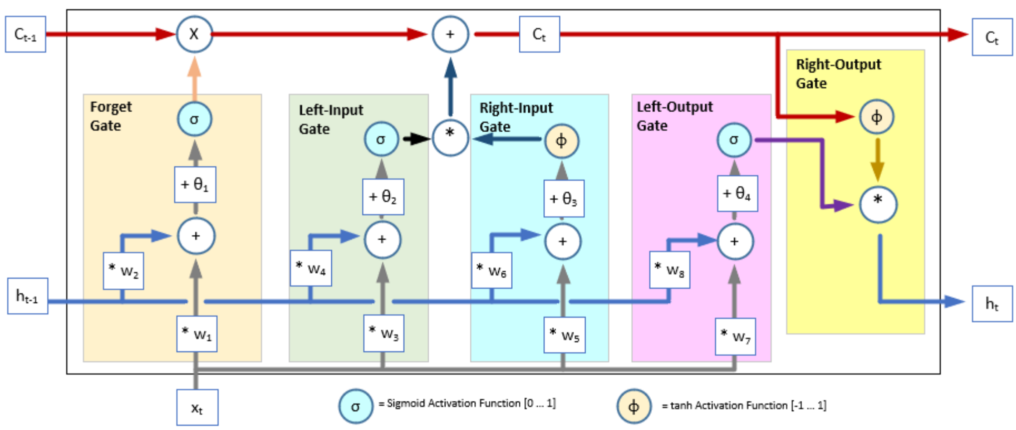

Fig. 4. LSTM model scheme

Rys. 4. Schemat modelu LSTM

Inside the forget gate, the input is taken from the input data (x_t) and the previous hidden state (h_{t-1}), so it can be described in this phase how the short-term will be maintained or eliminated. The forget gate formulation with weight adjustment (w_t) and bias (θ_t) can be defined as follows

$$f_t = \sigma\left(w_t \cdot \left[h_{t-1}, x_t\right] + \theta_t\right) \tag{14}$$

Furthermore, the left input gate:

$$i_t = \sigma\left(w_i \cdot [h_{t-1}, x_t] + \theta_i\right) \tag{15}$$

right-input gate:

$$\tilde{C}_t = tanh\left(w_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{16}$$

output gate:

$$o_t = \sigma\left(w_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{17}$$

$$h_t = o_t \cdot tanh\left(C_t\right) \tag{18}$$

LSTM has hidden-state (h_t) that represents the influence of short-term and overall states inside the model, while the cell state (C_t) describes long-term memory that can affect the hidden state or overall state.

2. Research methodology

2.1. Dataset description

We use two datasets that are the main benchmark oil prices globally: WTI and Brent crude spot prices. WTI crude oil is sourced from Texas, Louisiana, and North Dakota in the United States, while Brent crude oil is sourced from the North Sea in Europe, including Ekofisk, Forties, and Oseberg. The data set (USD per barrel) comes from Trading Economics, an American Company, which provides a historical database from official sources (the World Bank, the International Monetary Fund, government central banks, and national statistical offices) (Brent Crude Oil Summary 2022; Spot Crude Oil Price: WTI 2022). The data are daily prices from January 4, 2000, to June 17, 2022, amounting to 5768, and only on working days.

Table 2 shows that the max Brent oil price during that period was 146.08, with a mean of 65.32 and a standard deviation of 29.38. As for WTI crude oil, the max price was 145.29, almost similar to Brent oil.

TABLE 2. Descriptive statistics

TABELA 2. Statystyki opisowe

Attributes	Brent Oil	WTI Crude
Mean	65.32	61.35
Std Dev	29.38	25.57
Min	17.68	17.45
Max	146.08	145.29
25%	42.72	42.87
50%	62.33	55.57
75%	84.06	81.24

2.2. Forecasting model description

The data set is divided into 80% training and 20% testing. Every *n*-step in testing will be done by training on $\{x_1, x_2, \ldots, x_T\}$, prediction $\left\{\hat{x}_{T+1}, \hat{x}_{T+2}, \ldots, \hat{x}_{T+n}\right\}$, then for the next *n*-step, the training data will be added with $\{x_1, x_2, \ldots, x_T, x_{T+1}, \ldots, x_{T+n}\}$ and the next prediction $\left\{\hat{x}_{T+n+1}, \hat{x}_{T+n+2}, \ldots, \hat{x}_{T+2n}\right\}$, and so on until the end of the dataset. The training dataset process is illustrated in the description in Figure 5, where the entire training dataset enters the CEEMDAN process and is split into multiple *imfs*; CEEMDAN has the ability to accumulate *imf* values without residuals. For the *i* number of the *imf*, the *i* number of CNN_LSTM is also created, and from each forecasting model, the imf training data is reduced to the CNN model, and then each CNN data output becomes

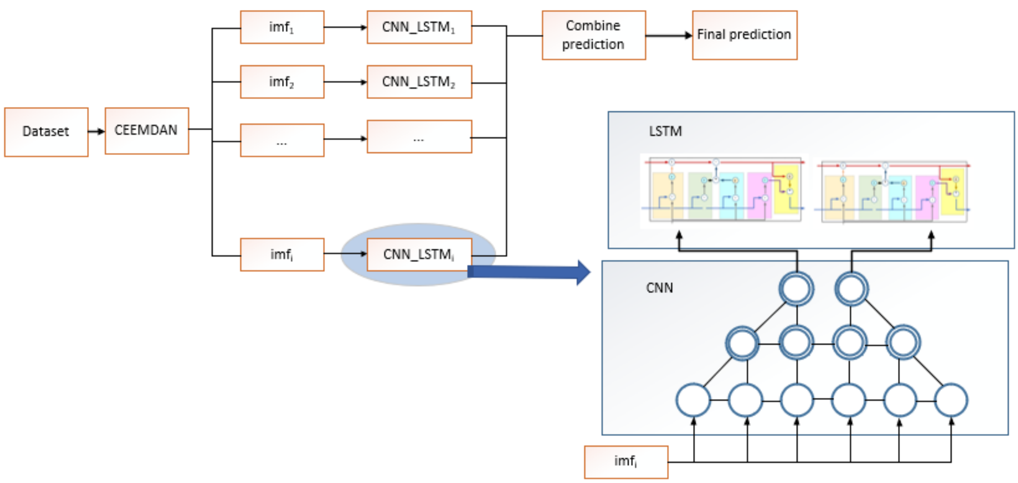

Fig. 5. CEEMDAN_CNN_LSTM

Rys. 5. CEEMDAN_CNN_LSTM

the input of the LSTM model sequentially. For the n-step forecasting process, we use the multiple output forecasting technique, which uses a single model to detect the training data set and outputs a single n-output with only a single computation, thus reducing the computational cost. The model uses Python 3.7 and is available at Git Hub (https://github.com/HerryKG/CEEMDAN_CNN_LSTM-for-crude-oil-price) with the raw data.

2.3. Error measurement

In the last step, to determine the capability of the model prediction result $\{\hat{x}_{t+n}\}$, we use the following parameters for evaluation. Where $e_t = error = x_t - \hat{x}_t$, and n is the number of training data. Since $x_t >> 0$ and has a natural zero, MAPE is applicable in this case.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|e_t\right| \tag{19}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left[e_t\right]^2} \tag{20}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|re_t(1)\right| = \frac{1}{n}\sum_{t=1}^{n}\left|\left(\frac{e_t(1)}{x_t}\right)100\right| \tag{21}$$

3. Study results and discussion

3.1 Measurement error analysis

The analysis of this paper will explain the sum error measurement of each n-step of the prediction. The characteristics of MAE, MAPE, and RMSE are lower-better. According to Lewis (1982), a MAPE value (< 10) is classified as a highly accurate forecast, (10 <= MAPE < 20) indicates a good forecast, (20 <= MAPE < 50) indicates a reasonable forecast, and (50 <= MAPE) indicates an inaccurate forecast.

Table 3 shows the results of the error measurements between 3 different decomposition models, namely EMD_CNN_LSTM, CEEMDAN_CNN_LSTM, and CNN_LSTM (without decomposition). It can be seen that in the analysis of Brent oil, from 60-step to 90-step, the process without CNN_LSTM decomposition has a much larger error at all steps, the deviation in MAE and RMSE on EMD_CNN_LSTM and CEEMDAN_CNN_LSTM is also seen far with MAE

Table 3. Comparison of the CNN_LSTM model with and without the decomposition process

Tabela 3. Porównanie modelu CNN_LSTM z procesem dekompozycji i bez niego

	Brent Oil			Crude WTI Oil		
	EMD_CNN_LSTM	CEEMDAN_CNN_LSTM	CNN_LSTM	EMD_CNN_LSTM	CEEMDAN_CNN_LSTM	CNN_LSTM
60-step						
MAE	4.3503	3.9354	7.2171	2.6803	2.0681	4.7632
RMSE	5.8449	5.6461	9.9009	4.3877	2.9637	6.6192
MAPE	7.1551	6.8242	13.7431	4.419	3.4044	8.2044
70-step						
MAE	5.1905	4.1063	7.7308	3.4411	2.1396	5.6178
RMSE	7.1350	6.3455	10.5192	5.1286	3.1074	7.4618
MAPE	9.6314	7.7769	14.5922	6.0166	3.5246	9.8118
80-step						
MAE	5.3327	4.5334	8.4266	3.3890	2.2725	5.2692
RMSE	7.0564	6.0062	12.0501	5.2355	3.1011	8.0631
MAPE	9.5181	7.8474	16.6563	5.9069	3.8107	8.8571
90-step						
MAE	6.2861	5.477	9.834	2.9820	2.8777	6.6742
RMSE	8.6165	7.2225	13.2162	4.2974	4.0796	8.6574
MAPE	11.285	9.6366	19.4585	4.9463	5.1023	11.2286

and RMSE on CNN_LSTM. During the comparison between the two decomposition techniques, the error value of CEEMDAN_CNN_LSTM is (MAE and RMSE) smaller for all steps in the table. As for the WTI crude oil data in Table 3, the error values of CEEMDAN_CNN_LSTM are also smaller than those of EMD_CNN_LSTM and the non-decomposition technique (CNN_LSTM). One of the advantages of the CEEMDAN is that it reduces the problem of mode mixing and adaptive noise implementation, which EMD does not have.

Table 4 compares three popular deep learning models when paired with the CEEMDAN technique: Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and CNN_LSTM. The measurement error value of CEEMDAN_CNN_LSTM gives a lower value than CEEMDAN_ANN and CEEMDAN_CNN on the Brent oil data set and the WTI crude oil price.

This can be seen in the line plot in Figure 6 for the Brent oil price and Figure 7 for the WTI crude oil price. The line RMSE of CEEMDAN_CNN_LSTM is always lower than that of CEEMDAN_ANN and CEEMDAN_LSTM, as well as the MAE value, which is always lower than other models for seven different experimental steps. As for the MAPE value, CEEMDAN_CNN_LSTM has a lower value than the other two models. The MAPE value for the Brent oil price is <10, which can be classified as a highly accurate prediction (Lewis 1982).

TABLE 4. Comparison between deep learning ANN, CNN, and CNN_LSTM models

TABELA 4. Porównanie modeli głębokiego uczenia ANN, CNN i CNN_LSTM

	Brent Oil			Crude WTI Oil		
	CEEMDAN_ ANN	CEEMDAN_ CNN	CEEMDAN_ CNN_LSTM	CEEMDAN_ ANN	CEEMDAN_ CNN	CEEMDAN_ CNN_LSTM
60-step						
MAE	4.1546	4.0088	3.9354	2.1693	2.2946	2.0681
RMSE	5.8141	5.9634	5.6461	3.2946	3.2960	2.9637
MAPE	7.1475	6.7684	6.8242	3.5981	3.8299	3.4044
70-step						
MAE	4.14	4.1067	4.1063	2.3249	2.2720	2.1396
RMSE	6.5231	6.9411	6.3455	3.3119	3.3562	3.1074
MAPE	7.8166	7.8588	7.777	3.9709	3.7669	3.5246
80-step						
MAE	4.8172	4.7432	4.5334	2.4657	2.5321	2.2725
RMSE	6.4454	6.6593	6.0062	3.3173	3.4659	3.1011
MAPE	8.3658	8.4528	7.8474	4.2363	4.2132	3.8108
90-step						
MAE	6.2828	5.7871	5.477	3.0223	2.9713	2.8777
RMSE	8.5733	8.2164	7.2225	4.347	4.3624	4.0796
MAPE	11.1748	10.2813	9.6366	5.315	5.0587	5.1023

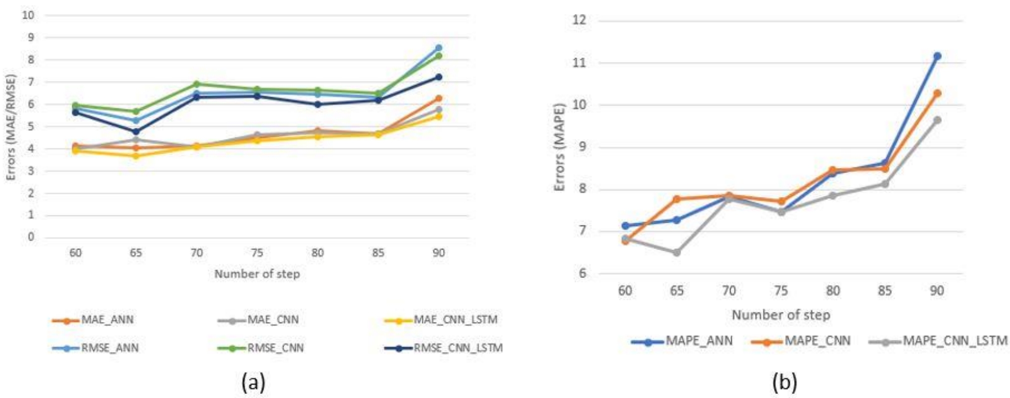

Fig. 6. Line plot measurement error – Brent oil price (a) MAE and RMSE, (b) MAPE

Rys. 6. Błąd pomiaru wykresu liniowego – cena ropy Brent (a) MAE i RMSE, (b) MAPE

Similarly, the measurement error line plot in Figure 7 is an interpretation of the WTI crude oil price, where the MAE and RMSE line plot values of CEEMDAN_CNN_LSTM have lower values than the other two deep learning models, implying a lower MAPE value.

MAPE values between 3 and 6 for the WTI crude oil price prediction in the CEEMDAN_CNN_LSTM model indicate that it is good enough to make predictions for the medium-term range (all-step prediction). This is a very good value for illustrating the robustness of the CEEMDAN_CNN_LSTM model.

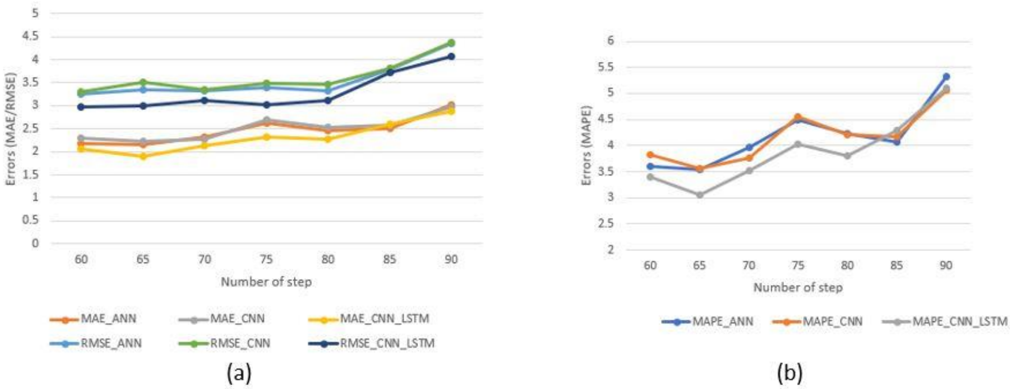

Fig. 7. Line plot measurement error – crude WTI oil price (a) MAE and RMSE, (b) MAPE

Rys. 7. Błąd pomiaru wykresu liniowego – cena ropy naftowej WTI (a) MAE i RMSE, (b) MAPE

3.2. Box plot analysis of the simulation model

In order to prove the ability of deep learning to predict the prediction results, we used 30 repetitions of simulations with always different RMSE values. The low RMSE quartile range value shows the reliability of the prediction model, and one of the appropriate tools to represent this is the box plot found in Figure 8 (Brent oil price) and 9 (Crude oil price). This range value occurs because the initial weight (w_0) and initial bias (θ_0) in the above Eq. (14) are different at each iteration performed, although the gradient descent process provides a final weight and bias value process that is close to optimal, the final result still has a different gap at each iteration. The box plot provides an overview of the range of RMSE values between the upper and lower quartiles. It can be seen in Figure 9 and 10 that the higher the prediction step, the higher the RMSE value tends to be. This is because the higher the n, the greater the predictive ability of the model and the greater the tendency for measurement error. Looking at Figure 8, the box height of the four steps is below 0.2 (<0.2), indicating that the range of RMSE values is below 0.2, with a mean data value of 65.32 (in Table 2 above) indicating that the range of RMSE output from the model is still relatively low.

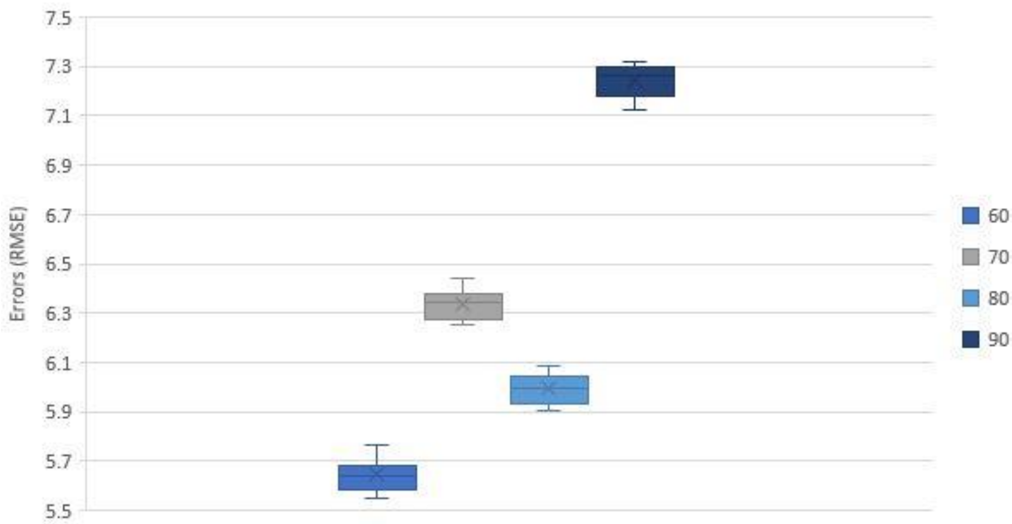

Fig. 8. Box plot RMSE simulations of Brent oil price

Rys. 8. Wykres pudełkowy symulacji RMSE ceny ropy Brent

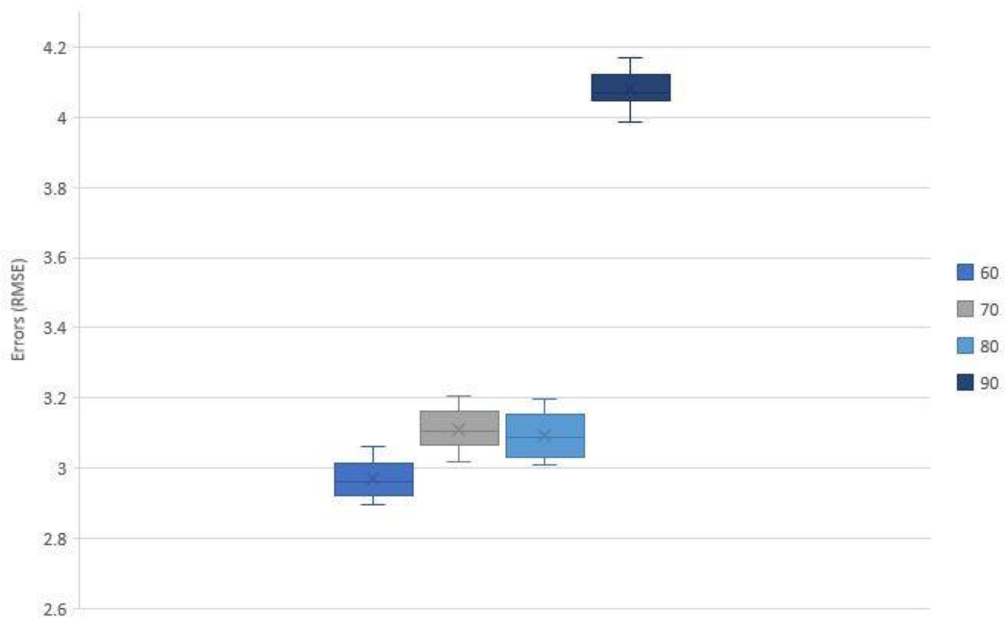

Fig. 9. Box plot RMSE simulations of crude WTI oil price

Rys. 9. Wykres pudełkowy symulacji RMSE ceny ropy naftowej WTI

For Figure 9, the RMSE box plot of the CEEMDAN_CNN_LSTM model on the crude oil price, where n = 90, the RMSE value is between the lower quartile = 4.02 and the upper quartile = 4.12. The range between the quartiles in this box plot is around 0.01, which is low when the mean of the WTI crude oil price data is 61.35.

c. Actual vs. Prediction Plot

For the prediction line plot results with the actual WTI crude oil price, see Figure 10, where the prediction (blue line) follows the actual (yellow line). The CNN_LSTM model can detect the next n-prediction with the pattern recognition factor owned by CNN and the long-term effect owned by LSTM from the training process.

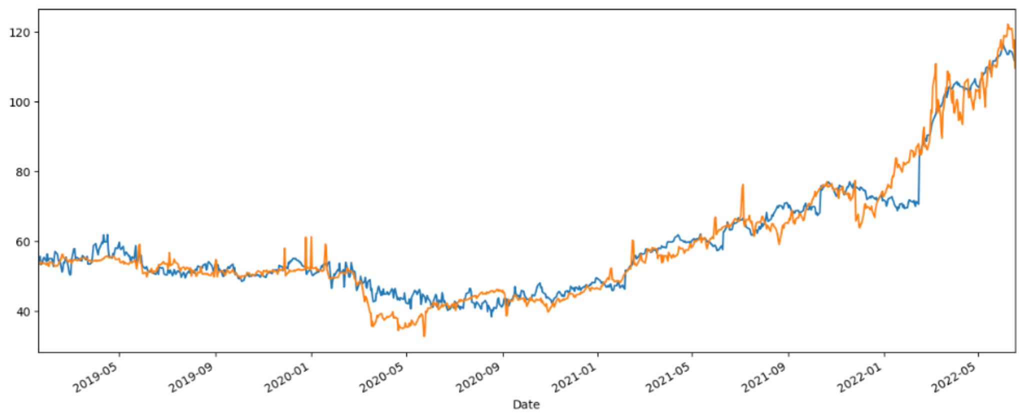

Fig. 10. Actual (orange) vs predictions (blue) of crude WTI oil price

Rys. 10. Rzeczywista (pomarańczowa) i prognozowana (niebieska) cena ropy naftowej WTI

Conclusion

As the main energy source for transportation fuel, forecasting tools can help businesses and related industries observe the possibility of significant changes in crude oil spot prices. Our motivation is to improve forecasting techniques for crude oil prices that can provide high accuracy for the medium-term forecasting category.

Therefore, we choose a decomposition technique that can anticipate the weaknesses of the previous empirical mode decomposition (EMD) technique, namely CEEMDAN. For the prediction model, we take two developments of deep learning models with their respective advantages, namely Convolutional Neural Network (CNN) to reduce the number of learning inputs and detect features in the learning inputs, with a combination of LSTM used to output prediction with the ability to maintain the influence of long term and short-term inputs.

Using the parameters RMSE, MAE, and MAPE as indicators of model accuracy, the proposed model provides much better values than no decomposition or other decompositions. In addition, the CNN_LSTM combination provides superior error measurement results compared to other deep learning models, such as ANN and CNN on Brent and WTI crude price data. The MAPE analysis shows that this model can maintain a relatively high value of less than 10 (< 10) for WTI and Brent oil prices when forecasting 60 to 90 steps. This shows that the forecasting model is robust for medium-term forecasting. In the box plot simulation, the forecasting model provides a quartile range between 0.1 and 0.2, which shows that the variance of this model is low.

This result shows progress in using deep learning as a reliable forecasting method. Decomposition can also increase the accuracy of the model. To improve further, new decomposition techniques, such as ICEEMDAN (Improve CEEMDAN) and the Gated Recurrent Unit (GRU) technique, which is a development of LSTM, can be introduced.

The Authors have no conflicts of interest to declare.

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Średniookresowe prognozowanie cen ropy naftowej przy użyciu hybrydowego modelu głębokiego uczenia CEEMDAN i CNN_LSTM

Streszczenie

Prognozowanie cen ropy naftowej zawsze było przedmiotem dyskusji wśród ekspertów ds. energii. Ze względu na znaczną zależność światowej gospodarki od ropy naftowej, zmienność ceny spot może mieć wpływ na podaż i popyt na rynku. Ponadto ropa naftowa jest nadal podstawową energią dla transportu na całym świecie. Chociaż odnawialne źródła energii znacznie się rozwinęły, ropa naftowa dominuje w paliwach transportowych w ciągu ostatnich kilku dekad. Niniejsze badanie koncentruje się na prognozowaniu wieloetapowym w średnim okresie i dostarcza model prognostyczny, który zapewnia solidną prognozę na 60 do 90 kroków do przodu. Głównym celem jest opracowanie modelu prognostycznego, który może utrzymać wysoką dokładność i niskie błędy. Niniejsza analiza wykorzystuje hybrydowy model uczenia głębokiego *Complete Ensemble Empirical Mode Decomposition with Adaptive Noise* (CEEMDAN) i model uczenia głębokiego *Convolutional Neural Network, Long Short-Term Memory* (CNN_LSTM). Dzięki połączeniu tych trzech różnych technik jesteśmy w stanie identyfikować cechy (trend i sezonowość) w uczeniu się danych historycznych i zapewniać wysoką dokładność prognozowania w przypadku prognozowania na następny okres. W artykule porównano proponowany model z innymi technikami dekompozycji i głębokiego uczenia. Proponowany model wykazuje niższe wartości średniego błędu bezwzględnego (MAE) i średniego błędu kwadratowego (RMSE) niż inne modele referencyjne dla cen ropy Brent i ropy *West Texas Intermediate* (WTI) – średni błąd procentowy bezwzględny proponowanego modelu (MAPE) skutkuje lepszym prognozowaniem z wartościami MAPE od 4 do 10. Symulacja z analizą wykresu pudełkowego daje również wartość zakresu kwartylowego poniżej 0,2, co pokazuje stabilność modelu w każdej iteracji. Wreszcie, proponowany model może zapewnić solidny model prognostyczny do wieloetapowego prognozowania średnioterminowego.

Słowa kluczowe: prognozowanie, cena ropy naftowej, kompletny rozkład trybu empirycznego zespołu z adaptacyjnym szumem, sieć neuronowa splotowa, pamięć długo-krótkotrwała