THE APPLICATION OF EEMD AND NEURAL NETWORK BASED ON POLAK-RIBIÉRE CONJUGATE GRADIENT ALGORITHM FOR CRUDE OIL PRICES FORECASTING

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ABSTRACT

Forecasting crude oil prices is very difficult to do because it has nonlinear and nonstationary characteristics. This research proposes a crude oil prices forecasting using a combination of EEMD and neural network. EEMD was used to decompose the price of crude oil into several IMFs and one residue. Before the training and testing was processed using FNN, EEMD output is normalized to fulfill network activation function. Data pattern of neural network was determined based on the results of normalization. The Learning method of neural network was based on Polak-Ribiére Conjugate Gradient algorithm. The output of neural networks on each component IMFs and the residue was aggregated using Adaline. The last process is denormalization of the Adaline output. Output of denormalization is the end result of the crude oil price forecasting. After forecasting results has been known, it then compared with the results of several neural networks learning algorithm. The result shows that the proposed method has better forecasting ability. This is indicated by the error value which was smaller than other forecasting algorithms for crude oil price forecasting.

Keywords: Crude Oil Price, Forecasting, EEMD, PCG, Adaline.

INTRODUCTION

The effect of crude oil prices have a large impact on the global economy. The prices will affect the financial markets, the price of fuel, and the price of goods and services (Haidar, et.al, 2008). Decline in crude oil prices will impact the budget deficit for oil exporting countries (Abosedra, Baghestani, 2004). The Fluctuations of crude oil market has a characteristics of nonlinear and nonstationary, so it is very difficult to forecast. The forecasting has important role in decision making such as: macro-economic policy (Xu and Ouenniche, 2012; Chang, 2012), financial stability (Azadeh et al.,2012; Naifar and Dohaiman, 2013), investment (Elder and Serletis, 2009), risk management and portfolio management (Reboredo and Castro, 2013). Additionally, forecasting aimed to reduce the impact of price fluctuations. The Research of forecasting crude oil prices which involves a combination of Ensemble Empirical Mode Decomposition (EEMD) and neural networks have been carried out by Herawati and Latif (2015). Resilient Backpropagation (Rprop) is used as an artificial neural learning. However, the algorithm Rprop takes a long time in the learning process. The research of crude oil prices has also carried out by Chatrath, et.al (2015), Priyadarshini (2015), Knetsch (2007).

This research proposes a crude oil prices forecasting using a combination of EEMD and neural network. The Learning method of neural network was based on Polak-Ribiére Conjugate Gradient (PCG). The PCG Algorithm is faster and has higher quality of separation and a lower cost in computational than others (Ghasemi-Fard, 2013). The Combinations of these methods have not been done in the case of crude oil price forecasting previously. The combination of EEMD and neural network based on PCG is intended to improve the weaknesses of the learning process in previous research.

LITERATURE REVIEW

Crude Oil Prices

World crude oil prices are determined based on the three benchmarks such as West Texas Intermediate (WTI), Brent and Dubai. WTI was used in the United States for industrial gas. Brent is the value of standardization in crude oil prices worldwide, especially used in Europe and OPEC market. Dubai is a product consisting of crude from Dubai, Oman or Abu Dhabi. Dubai is the main reference for Persian Gulf oil to be shipped to Asian markets. Based on data from the US Energy Information Administration stated that there were significant price increases for the price of WTI and Brent crude oil. In early 2003, the price of WTI is 32.95 US dollars per barrel, while the price of Brent is 31.18 US dollars per barrel. Price increases continue to occur until mid-2006, WTI through the price 74.41 US dollars per barrel, while the price of Brent reached 73.67 US dollars per barrel. The fluctuation of crude oil prices is influenced by many factors. According to Stevens (1995), demand and supply are also factors that affect the movement of crude oil prices. Fluctuations also very much influenced by the events of the past, present, and future irregular, such as weather, stock levels, the growth of GDP (Gross Domestic Product), political aspects and psychological expectations people (Yu et al, 2008). Based on the impact and the factors that affect the movement of crude oil price, the price forecasting is very necessary. Forecasting is used to reduce the impact of price fluctuations. Additionally, forecasting helps investors and individuals in making decisions related to the energy market.

Ensemble Empirical Mode Decomposition (EEMD)

EEMD is a data processing method of nonlinear and nonstationary (Wu and Huang, 2004). EEMD have a basic idea that any observed data is the combination of time series and the right noise. In fact, the average time series ensemble approach which is true if the data collected by the observation that a separate and different noise levels. Therefore, an additional step was taken with the addition of white noise to extract the correct signal in the data. White noise is a random signal having a frequency distributed evenly throughout the frequency range. The addition of white noise will fill the space evenly corresponding time frequency components that make up the signal with different scales. Components of different scales are automatically projected on a scale appropriate to the specified reference white noise. Procedure of crude oil prices decomposition using algorithms EEMD as follows:

a. Add a series of white noise into time series data.
b. The data is decomposed into some IMFs and one residue component.
c. Repeat steps a and b with different white noise for each time series data. The final result is obtained from the ensemble decomposition stating IMFs and residue appropriate.

Polak-Ribiére Conjugate Gradient (PCG)

Polak-Ribiére Conjugate Gradient is one of the learning neural network proposed by Polak and Ribiere. This algorithm searches the negative value of the gradient network since the first iteration and based on the direction conjugation. The algorithm of *Polak-Ribiére Conjugate Gradient* used is based on research Polak and Ribière (1969).

METHODOLOGY

The methodology in this research is shown in Figure 1.

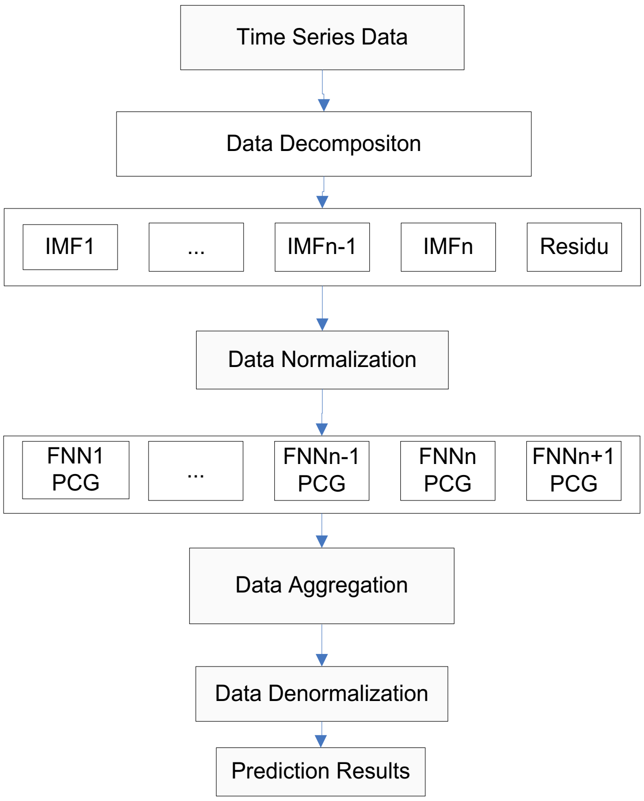

Figure-1. Methodology

Data Exploration

The research used monthly data time series of crude oil prices on the website of energy information administration (EIA) USA http://www.eia.doe.gov, that is West Texas Intermediate (WTI) and Brent. WTI data used were from January 1986 until January 2015 with a total of 349 data, while Brent data used were from May 1987 until January 2015 with a total of 333 data. Based on the two types of data, 85% data was used in the training process to construct forecasting models, while the remaining 15% data was used for testing the performance of the forecasting model. Mean Square Error (MSE) and Root Mean Squared Error (RMSE) was used to measure the accuracy of the forecasting performance. MSE and RMSE equation as shown in equation (1) and 2). A_t is the actual data at time t, where Ft is forecasting data at time t, and n is the number of data.

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2 \quad (1)$$

$$\mathrm{RMSE} = \sqrt{\sum_{t=1}^{n}(F_t - A_t)^2} \quad (2)$$

Data Decomposition

EEMD was used to decompose the international crude oil prices data into several IMFs and one residu. Number of ensemble members is set at 100 and the standard deviation of the white noise is set at 0.2. The decomposition process using parameter values-threshold-1 is 0.05, values-threshold-2 is 0.5, and the tolerance limit is 0.05.

Data Normalization

Data normalization was conducted to satisfy the requirements activation function neural network. The data was normalized using equation 3 (Kaastra and Boyd, 1996).

$$x' = TF_{min} + (TF_{max} - TF_{min}) \times \left(\frac{x - D_{min}}{D_{max} - D_{min}}\right) \quad (3)$$

Where the variable x' is the result of data normalization, TF_{min} and TF_{max} is a minimum value and a maximum range of activation function, x is the actual time series data to be normalized, D_{min} and D_{max} is a minimum value and a maximum value of the actual time series data.

FNN with Polak-Ribiére Conjugate Gradient

Data pattern of neuron input, hidden and output of the network was determined based on the results of data normalization. Data are divided into two types, that is training and testing data. The training process will stop if the number of iterations reach the maximum value or the specified error value has been reached. Meanwhile, the testing process performed on the input data that has never been trained before. Testing data using the weights and biases of the results of the training FNN.

Data Aggregation

The testing results for all IMFs and residue was agregated using adaline. This process will produce the forecasting. The last process was denormalization of the Adaline output. Denormalization was used to restore data into real value.

RESULTS AND DISCUSSIONS

Result of decomposition using Ensemble Empirical Mode Decomposition algorithm is shown in Figure 2 for WTI data and Figure 3 for Brent data. Comparison of forecasting performance using PCG Learning with some artificial neural network learning algorithm is shown in Table 1 and Table 2, respectively for WTI and Brent.

Experiment begins with decomposing data using EEMD. Furthermore, the data of each IMF and the residue was normalized to fulfill activation function of FNN. Network architecture data patterns used is 6-10-1 (six input neurons, ten hidden neurons and one output neuron). FNN experiments performed iteration process as much as 10,000 times, learning rate value is 0.1, and error tolerance value is 0.0001. The final step is aggregating all the FNN output using adaline to generate forecasting. Then, determining the performance of the forecasting was done by finding the value of RMSE and MSE. After forecasting results using the PCG has been known, it was compared to the results of several neural network learning algorithm, such as Gradient Descent Backpropoagation (GDBP), Gradient Descent with Adaptive Learning Rate Backpropagation (GDALR), Levenberg - Marquardt Backpropagation (LMBP), Gradient Descent with Momentum Backpropagation (GDM), Gradient Descent with Momentum and Adaptive Learning Rate Backpropagation (GDMALR), Conjugate Gradient Backpropagation with Fletcher Reeves Updates (CGF), Powell-Beale Restarts (CGB), Batch training with weight and bias learning rules (B), Resilient Backpropagation (RPROP), Scaled Conjugate Gradient (SCG) and One Step Secant Algorithm (OSS).

Table 1 shows the best performance of WTI data gained from PCG learning algorithm with RMSE value is 0.04932 and the MSE is 0.00243. Meanwhile, the data Brent as shown in Table 2, showed that the best result was obtained with RMSE and MSE are respectively 0.04985 and 0.00249. In this research, RMSE and MSE is the main measure in assessing the performance of forecasting. Forecasting performance will be concluded to be good if it has a small error value. Forecasting performance using EEMD and neural networks with PCG learning algorithm is shown in Figure 4 and Figure 5, respectively for WTI and Brent. Both of these figures using testing data and showed a fairly accurate proximity to the actual crude oil prices data.

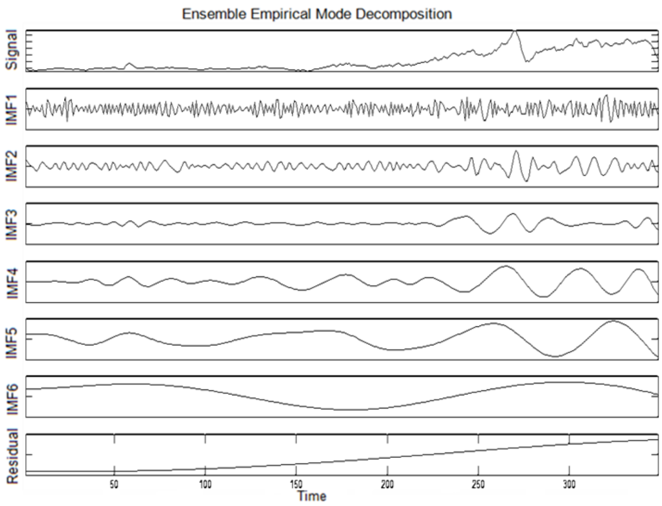

Figure-2. Decomposition Result of WTI Data

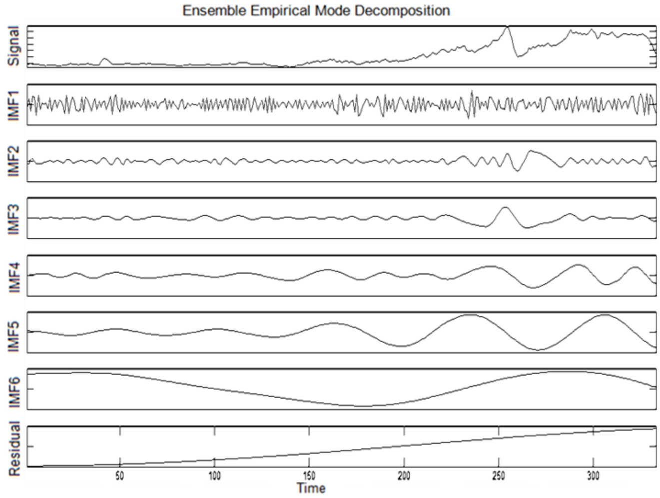

Figure-3. Decomposition Result of Brent Data

Table-1. Comparison of forecasting performance use WTI

Algorithm	RMSE	MSE
GDBP	0,05930	0,00350
GDALR	0,06890	0,00470
LMBP	0,05420	0,00290
GDM	0,05556	0,00309
GDMALR	0,05253	0,00276
CGF	0,05176	0,00268
PCG	**0,04932**	**0,00243**
CGB	0,05893	0,00347
B	0,05798	0,00336
RPROP	0,05410	0,00293
SCG	0,05137	0,00264
OSS	0,05051	0,00255

Table-2. Comparison of forecasting performance use Brent

Algorithm	RMSE	MSE
GDBP	0,05416	0,00293
GDALR	0,05306	0,00281
LMBP	0,05140	0,00264
GDM	0,05827	0,00339
GDMALR	0,05452	0,00297
CGF	0,05388	0,00290
PCG	**0,04985**	**0,00249**
CGB	0,05904	0,00349
B	0,06053	0,00366
RPROP	0,05191	0,00269
SCG	0,05637	0,00318
OSS	0,05330	0,00284

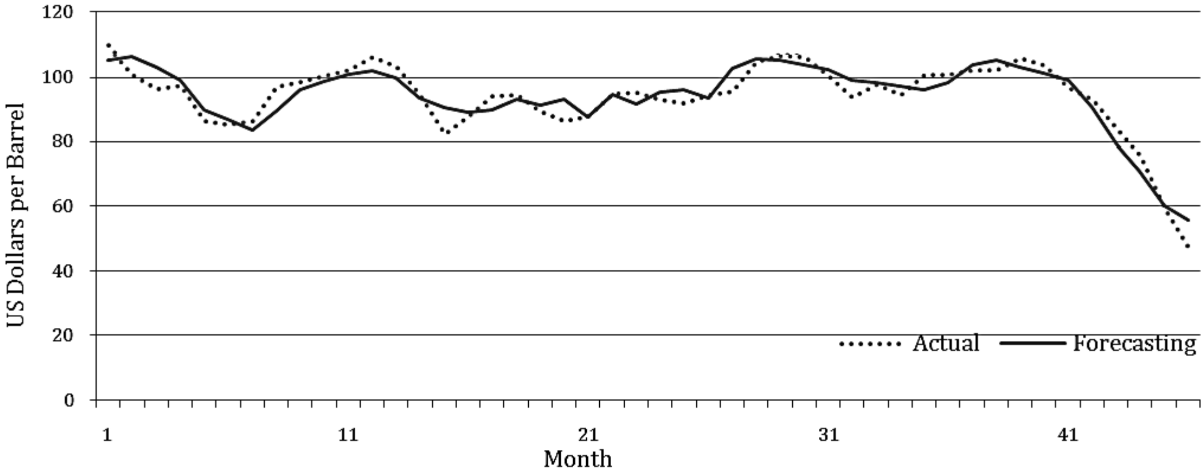

Figure-4. Comparison between forecasting results and actual data for WTI

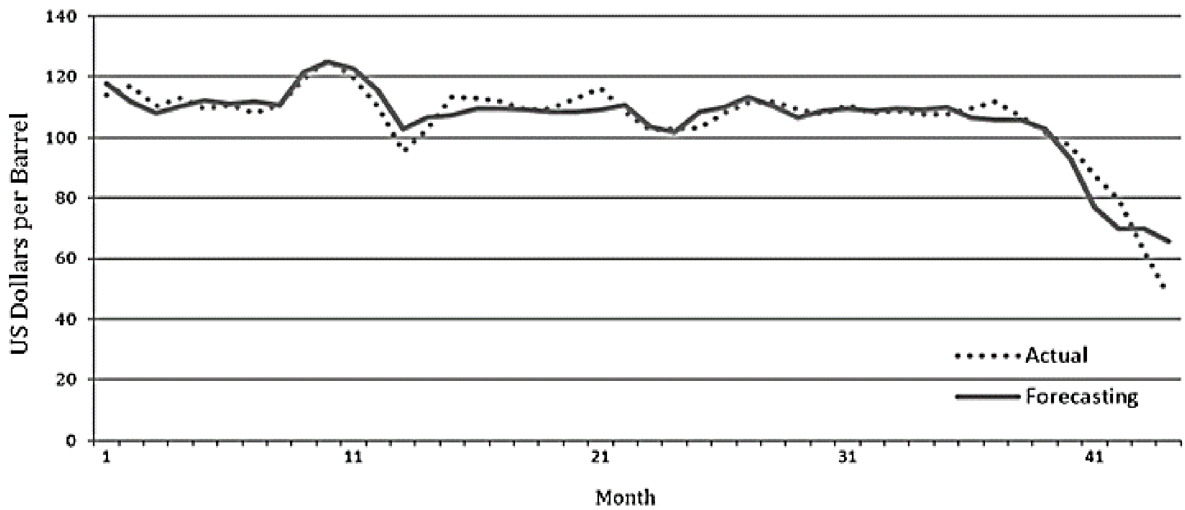

Figure-5. Comparison between forecasting results and actual data for Brent

CONCLUSIONS

According to the experiments, it can be concluded that the method of EEMD and neural network based on Polak-Ribiere Conjugate Gradient algorithm generates better RMSE and MSE than other artificial neural network learning algorithms. Forecasting result shows that the best performance is obtained with RMSE and MSE values of 0.04932 and 0.00243, respectively, for WTI data. Meanwhile, experiments conducted using data Brent generates RMSE and MSE of 0.04985 and 0.00249, respectively.

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