Hybrid Method Based on Wavelet Transformation and Reinforcement Learning To Forecast Crude Oil Price

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Abstract:
Crude oil prices are usually not stationary and affected by several factors that affect supply and demand, so the process of estimating and forecasting the price is not clear. By relying on artificial intelligence, we can improve the prediction process. In the proposed research, the original data are processed using a moving average, which is one of the time series techniques used in forecasting processes and then use both reinforcement learning and wavelet transformation to perform improvements on the moving average method specialized in future forecasting. Where the optimization method is accomplished in two stages. First, Prices decomposition by Haar that one of the algorithms of the wavelet transformation, and the second stage is performed by Q-Learning, one of the most common reinforcement learning methods. By comparison between the results of the previous research and the proposed research, the results of hybrid methods are more accurate and effective than the other method research. Whereas, hybrid technologies take advantages of the combined methods.

Keywords: Q-learning,, Haar Wavelet, Moving Average, Reinforcement Learning, Wavelet transformation, Forecasting.

1. Introduction

Kim, M. S. (2018) Crude oil is one of the important minerals that humans need and has a major impact on the global economy and important source of energy, Volatility in oil prices leads to difficulties in the process of price prediction because it is affected by peace, war, supply and demand . **Xie, W. Yu, L. Xu, S. Wang, S.(2006)** There are many mechanisms and methods for conducting forecasting of crude oil prices, but it is difficult to obtain on high accuracy results because they are affected by political factors and general economic activities . **Azadeh,A Aramoon, M Saberi, M (2009)** One of these techniques that is used in forecasting is the moving average **. Mahdiani, M.R & Khamehchi, E (2016)** Most forecasting mechanics tried to use one of the techniques method for forecasting based on support vector machine (SVM) **, Han, J.B., Kim, S. H., Jang, M. H., & Ril, K. S., (2020)**Genetic Algorithm (GA) , **Kulkarni,S. & Haidar, I. (2009)** Artificial Neural Networks . **Kamei, K and Ishikawa, M. (2004)** usually hybrid techniques give more accurate results. **Hein, D., Udluft, S., & Runkler, T. A. (2018)** the researchers applied both Genetic Algorithm and NARX Neural Network to Forecast Daily Bit-coin Price and used the genetic algorithm to optimize the architecture of the NARX neural network . Proposed research will use combination model of both reinforcement learning and wavelet transformation to make a more accurate forecast of crude oil prices. The important idea of the study is how to use reinforcement learning and wavelet transformation together to analyze past real data and use the resulting data in the prediction processes.

The structure of the proposed paper consists of reinforcement learning and wavelet transformation in section 2 and section 3, then combining the two techniques together where the hybrid method is used for both Haar Wavelet with Q-Learning for the purpose of forecasting crude oil prices in section 5. After that extracts the experimental results as shown in section 6 and then the conclusion in section 7.

2. Reinforcement Learning (RL):

Afanasyeva, A. & Buzdalov, M. (2011) the agent performs a group of actions within a framework called the environment. This action creates an interaction between the agent and the environment. As in Figure (1). **Lee, J. W. (2001)** Reinforcement learning aims to maximize the sum of discounted future rewards given by the environment.

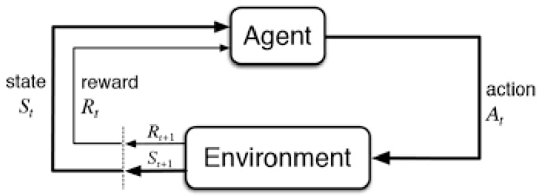

Figure (1): interact between Agent and Environment

Mehta, P. & Meyn, S. (2009) RL is concerned with how software agents ought to take actions in an environment in order to maximize their received accumulated rewards. In RL, the acting agent is not explicitly told which actions to implement. Instead, the agent must learn the best action strategy from the observed environment's reward in response to the agent's actions. Generally, such actions affect both the next reward and subsequent rewards . **Dayan, P.(1992**) The proposed research will use Q-Learning which is an algorithm of reinforcement learning. It takes the best action to give the current state based on Markov Decision Processes (MDPs). And at each time step t, a learning agent observes a state S at time t environment. Next, the agent selects an action A at next time step t+1, the agent transits to a state S_{t+1} and receives a reward R_{t+1} from the environment after each transition in Q-Learning equation.

2.1 Q-Learning:

Dearden, R., Friedman, N., & Russell, S., (1998) a form of reinforcement learning that relies on dynamic programming (DP). Castronovo, M. et al (2012) Uses to compute an optimal policy and basically depends on the Markovian technique. **Mignona, A. S. & Rocha, R., L. (2016)** it has proven to be effective for models with finite state and action space. **Alipourl, M., M., Raza, S.N., & Balafar, M. A. (2017) Q**-Learning is mainly based on the basic concepts Markov Decision Process MDPs that consists of 5-tuple (S, A, P, R, S_0) where S's a set of states, A is a set of actions. P is a probability transition from state to another state by a specific action, R means that the agent gets a reward at each time step according to R (S_t, A_t, S_{t+1}) and S_0 is a start state. Q (s, a) is updated using the following equation (1):

$$Q\,(s, a) \leftarrow [R+\gamma \max Q\,(s', a)] \qquad (1)$$

Afanasyeva, A. & Buzdalov, M. (2011) where s′ is a new state which transmitted to it. The agent performs a certain action from the current state to the next state, it gets a reward from the environment and in the Q-Learning algorithm the process of selecting the state based on the mechanism Greedy that works in two ways: exploitation and exploration, exploitation means that the agent selects the action that has the highest rewards and exploration means that the agent selects an action randomly. **Even-Dar, E. & Mansour, Y. (2003)** Exploitation is the best to receive a good reward right away. **Liu, D., Niu, D., Wang, H., & Fan, L.(2014)** γ is the discount factor ($0 < \gamma < 1$). The function Q (s, a) is the value associated to the action (s, a) and represents how well the choice of this action **Santos, J. P. Q., Junior, F. C. L., Melo, R.M.M. J. D., & Neto, A. D. D., (2009))** an optimal policy is a policy that can maximize the possible reward from a state, called value policy. **Liu, D., Niu, D., Wang, H., and Fan, L.(2014)** to interaction between the agent and the environment that is done by a specific series of actions, Q- Learning performs the action according to the optimal selection of a set of possibilities, So that the resulting value is the best.

3. Wavelet transformation (WT):

Kaboudan, M. (2004) it is an ideal way to analyze and process signals. **Alwadi, S. (2011)** WT usually decomposes a signal into an approximation component and many detail components.

Voronin, S. & Partanen, J. (2013) the original signal is decomposed into smooth coefficients and detail coefficients as in Figure (2). Which are represented by:

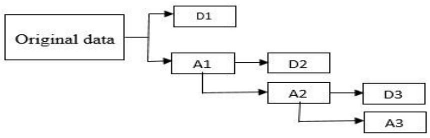

Figure (2): Dec omposed into smooth coefficients and detail coefficients

Where D's is smooth coefficients and A's is represents detail coefficients. **Sudibyo, U., Eranisa, F., Rachmawanto, E. H., Setiadi, D. R. I. M., & Sari, C. A. (2017)** the proposed model will use Haar wavelet transformation method to decompose of original data. **Alwakeel, M. & Shaaban, Z. (2010)** the wavelet transform convert the financial series in a set (typically three to six) of constitutive series. These series show a better behavior than original price series. In other hands, more stable in variance and no outliers. **Swaidan, W. & Hussin, A. (2014)** it deals with stable and unstable data and it adapts itself by certain mathematical transformations. In this study will uses composition new relation from both Q-learning and Haar transform.

3.1 Haar wavelet transformation (HWT):

Gurumoorthy, S., Muppalaneni, N. B., & Kumari, G. S. (2020) HWT technology is considered one of the wavelet transform methods that decomposes the signal and has the ability to improve data. **Shaarawy S. & Broemeling, L. (2007)** The wavelength must be an even number. Suppose the following time series:

$$m = m_1 + \cdots + m_n \qquad (2)$$

Where n is even.

HAAR technology splits m signal into two parts. The first is the average coefficient vector with components:

$$a_i = 2^{-1}[m_{2i-1} + m_{2i}] \qquad (3)$$

Where i=1, 2 ,…n/2 and the detail coefficient vector according following equation:

$$d_i = 2^{-1}[m_{2i-1} - m_{2i}] \qquad (4)$$

Where i =1, 2, … , n/2. Each term in the average vector represents average across a time scale and term in the detail vector represents variations between sequential values of the time series. These can be concatenated into another N-vector as a linear matrix transformation of m: h= [a | d]. Haar Wavelet is also ideally used for image processing and pattern recognition.

4. Moving average (MA):

Vandewalle, N., Ausloosa, M., & Boverouxb, Ph. (1999) A mathematical statistical method and consider a sequence of real random variables [32]. James, F. E. (2016) it is considered one of the important tools for analysis **.Holt, C. C. (2004)** MA is used to predict future values by analyzing the given data and creating a continuous series of averages according to a specific pattern**.** **Chandar, S. K., Sumathi, M., & Sivanandam, S. N. (2016)** usually this method is used to forecast future prices within specified time periods. This exploratory analysis indicates the great flexibility moving averages in dealing with forecasts. As in the equation (1).

$$\boldsymbol{X_i} = \frac{\boldsymbol{Y_i + Y_{i+1} + Y_{i+2} + \dots + Y_n}}{\boldsymbol{n}} \qquad (5)$$

Where X represents a Moving Average, i is a time series and Y is given data series. The first element of the moving average is obtained by taking the average of the initial fixed subset of the number series. Then the subset is modified by "shifting forward"; that is, excluding the first number of the series and including the next value in the subset.

5. Methodology:

Through reading of previous research, it became clear that the hybrid methods are more efficient and accurate than the single prediction methods. The proposed study, makes use of the characteristics of both wavelet transformation and the reinforcement learning to produce a highly accurate prediction model for forecasting oil prices. The proposed research, in the beginning prepare real historical data for crude oil prices and analyze them using time series techniques. The proposed model will use moving average method to decompose data for forecasting. In the second stage, pass the output of the time series (moving average) to the wavelet transformation technique (Haar wavelet) to decompose the outcome of the prediction process. The third stage is to replace the output of Haar wavelet and put it instead of Reward (R) in the Q-Learning equation (1). As following:

$$Q\ (s,\, a) \leftarrow [\text{Haar}+\gamma \max Q\ (s',\, a)] \qquad (6)$$

The work of the algorithm (1) begins processing the original data by the time series according to the moving average method, and then the resulting data series is processed by hybrid Q-learning and Haar wavelet technology. The transition from state to another according to E-Greedy method based on exploitation way to select optimal values where Q-learning function is making the current state takes the decision to move to another state by a specific action, and then get the expected reward.

Algorithm (1): hybrid Q-learning and Haar wavelet.

Input: real data set.
Output: forecast data set.
Step 1 Input real data set.
Step 2 Set Q(s, a) as zeros matrix.
Step 3 Processing real data set by time-series (Moving Average). As follows:
For i=1 to n, where n is number of values.
$X_i = \frac{Y_i+Y_{i+1}+Y_{i+2}}{3}$. In each iteration i =i+1 and stop condition when i = n.
Step 4 Decomposition output of (Moving Average) by Haar wavelet transform. The vector is decomposed into two parts according to equations (3) and (4) and then the output of those equations integrate with each other.
Step 5 Set outcome step 4 as rewards matrix.
Step 6 Select state S randomly.
Step 7 Take action a to another state s by using E-Greedy Policy and to get a reward (R) from the reward Matrix
Step 8 update
$Q\ (s,\, a) \leftarrow [\text{Haar}+\gamma \max Q\ (s',\, a)]$
Step 10 Repeating from step 7 to step 9. Until
If $Q(s□,a)_i=Q(s□,a)_{i-1}$ end repeating where **i =1, 2, 3 , . . ., n.**

6. Experimental results:

The need for a big data set is to build this the proposed model. This paper will uses Europe Brent Spot Price (Dollars per Barrel) and these data were taken from website (US Energy Information Administration) and to the interval from 1987 to mid-2018. Kwan, S.H. and Mertens, T.M. (2020) It seems clear that oil prices are non-stationary to the interval. See Figure (3) .Predicting the prices of crude oil is very difficult because it is affected by political, economic, environmental and health factors, the last of which was the Covid-19 pandemic [38]. By using artificial intelligence methods that helps to improve the performance of traditional statistical techniques. In this research, both reinforcement learning and wavelet transformation were combined to provide a more precision model, predicting future to oil prices using the moving average method and then improvement the outcome with Haar Wavelet and Q-Learning. Data set was programmed and processed by using Matlab.

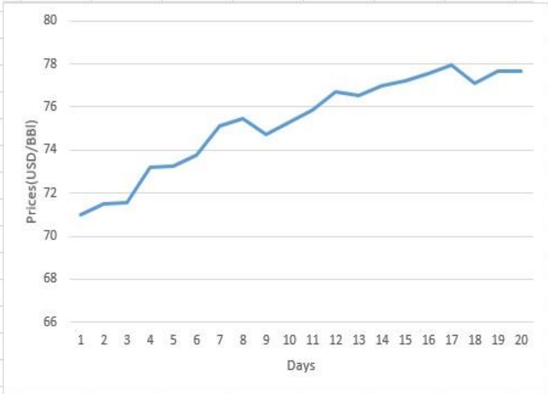

Figure (3): prices of real oil

From comparison of forecasting crude oil prices between the statistical methods based on Moving Average and the proposed model hybrid between Q-Learning and Haar Wavelet, it is clear that the proposed method is better and more accurate as shown in the figure (3). Comparison of the resulting data between Moving Average Technique and hybrid Haar Wavelet and Q-learning Technique. Note that the digital results of the Hybrid Method were also more accurate for the same period.

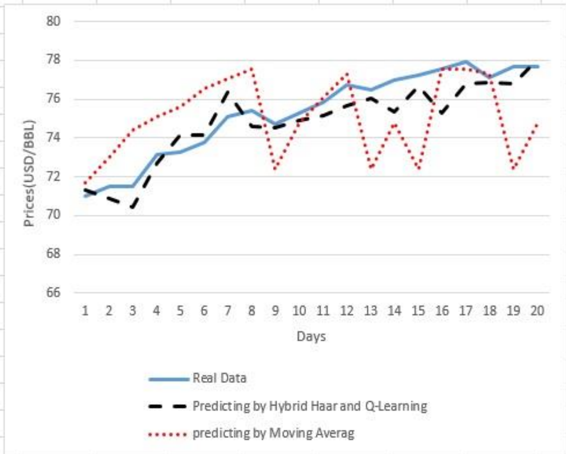

Figure (3): comparing between input data, Moving Average and hybrid Q-Learning with Haar Wavelet

Kulkarni, S. and Haidar, I. (2019) After the comparison between the research proposed in this paper and a previous study based on a single technology where the artificial neural network technology was applied to predict crude oil prices [39], it became clear that the hybrid method is more accurate and simulates the actual data as in Figure (4).

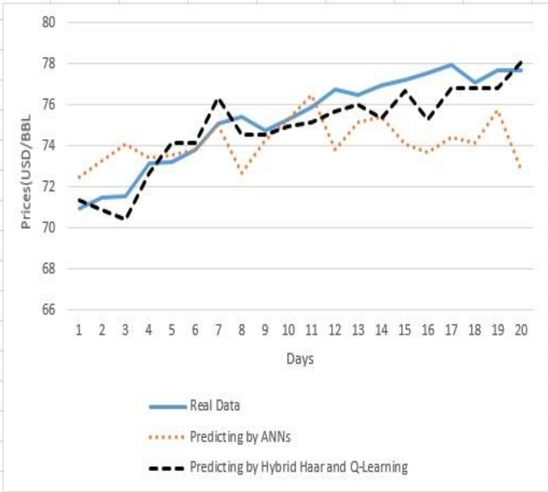

Figure (5): comparing between input data, predicting by ANN and predicting by hybrid Q-Learning with Haar Wavelet

Table (1): real prices and forecasting prices

input data	Predicting by ANNs	Diff. between input data and ANNs	Predicting by Hybrid Haar and Q-Learning	Diff. between input data and Hybrid Haar and Q-Learning
70.98	72.45	1.47	71.34	0.36
71.51	73.31	1.8	70.87	0.64
71.53	74.05	2.52	70.45	1.08
73.17	73.43	0.26	72.68	0.49
73.24	73.58	0.34	74.18	0.94
73.79	73.8	0.01	74.13	0.34
75.1	75.03	0.07	76.37	1.27
75.43	72.69	2.74	74.56	0.87
74.73	74.29	0.44	74.53	0.2
75.27	75.28	0.01	74.93	0.34
75.87	76.51	0.64	75.13	0.74
76.72	73.8	2.92	75.69	1.03
76.51	75.15	1.36	76.03	0.48
76.96	75.4	1.56	75.32	1.64
77.22	74.05	3.17	76.69	0.53
77.54	73.68	3.86	75.29	2.25
77.96	74.42	3.54	76.78	1.18
77.08	74.17	2.91	76.83	0.25
77.68	75.77	1.91	76.78	0.9
77.67	72.82	4.85	78.06	0.39

In Figure (5) and Table (1), the comparison between the results of Prediction by ANN and the hybrid method with real prices, through the results and the difference between these methods, it is clear that the hybrid technology gives better outputs than single method.

Artificial neural networks Prediction is based on multilayer feed-forward neural network to forecast crude oil spot price where the data is passing through three feed-forward networks layers for improving the input that produced by Moving Average (MA). As for experimental results to the proposed method is produced by training of 10.000 epoch and using γ = 0.04, using Q-Learning Technology after treating original data by MA and passes Haar technology to decomposed, then integrate into Q-Learning.

7. Conclusion:

The proposed research presents reinforcement learning and wavelet transformation to solve the problem of prediction accuracy. Using moving average time series for the purpose of forecasting oil prices. The help of artificial intelligence techniques to improve this traditional prediction methods. With the usage of Q-Learning and Haar wavelet approaches, the designed model is more efficient and accurate than other techniques used in crude oil price forecasting .Empirical results show that the proposed method is more useful for forecasting oil price. Where real prices are treated using a moving average, then the resulting data is analyzed by Haar Wavelet and then replaced by the reward matrix in the Q-Learning equation.

Rrferences

1. Kim, M. S. (2018) Impact of supply and demand factors on declining oil prices, Energy, vol. 155, pp. 1059-1065.
2. Dong, M. chang, C. P. Gong, Q. Chu, Y. (2019) Revisiting global economic activity and crude oil prices: A wavelet analysis, Economic Modelling, vol. 78, pp. 134-149.
3. Maharani, S. Widagdo, P. P. , Hatta, H. R. (2020) Forecasting Model of Amount of Water Production Using Double Moving Average Method, *International Conference on Computer and Informatics Engineering (IC2IE),* Yogyakarta, Indonesia, Sept 15-16 pp. 167-170.
4. Othman, A. H. A. Kassim, S. Rosman, R. B. Redzuan, N. H. B. (2020) Prediction accuracy improvement for Bitcoin market prices based on symmetric volatility information using artificial neural network approach, Journal of Revenue and Pricing Management, vol. 19, pp. 314-330.
5. Xie, W. Yu, L. Xu, S. Wang, S.(2006) A New Method for Crude Oil Price Forecasting Based on Support Vector Machines, International Conference on Computational Science, vol. 3994, pp. 444-451.
6. Azadeh,A Aramoon, M Saberi, M (2009) An integrated GA-time series algorithm for forecasting oil production estimation: USA, Russia, India, and Brazil, International Journal of Industrial and Systems Engineering, vol. 4, pp. 368–387, 2009.
7. Mahdiani, M.R and Khamehchi, E (2016) “A modified neural network model for predicting the crude oil price,” Intellectual Economics, Vol. 10 , pp. 71–77.
8. Han, J.B Kim, S. H. Jang, M. H. Ril, K. S.(2020)Using Genetic Algorithm and NARX Neural Network to Forecast Daily Bitcoin Price, Computational Economics, vol. 56, pp. 337–353, 2020.
9. Kulkarni,S. and Haidar, I(2009) Forecasting Model for Crude Oil Price Using Artificial Neural Networks and Commodity Futures Prices,(IJCSIS) International Journal of Computer Science and Information Security, Vol. 2, pp 81-88.
10. Kamei, K. Ishikawa, M. (2004) “Determination of the optimal values of parameters in reinforcement learning for mobile robot navigation by a genetic algorithm,” International Congress Series, Vol. 1269, pp. 193-196.
11. Hein, D. Udluft, S. Runkler, T. A. (2018) Interpretable policies for reinforcement learning by genetic programming, Engineering Application of Artificial intelligence, Vol. 76 , pp. 158-169.
12. Afanasyeva, A. Buzdalov, M. (2011) Choosing Best Fitness Function with Reinforcement Learning, the International Conference on Machine Learning and Applications, vol. 2, pp. 370-377.
13. Lee, J. W. (2001) ”STOCK PRICE PREDICTION USING REINFORCEMENT LEARNING,” IEEE, Pusan, Korea (South), June 12-16, 2001, pp. 690-695.
14. Mehta, P. Meyn, S.(2009) “Q-learning and Pontryagin’s Minimum Principle,” IEEE Conference on Decision and Control, Des. 15-18, 2009, pp. 3598-3605.
15. Dayan, P.(1992) Technical Note Q,-Learning, Kluwer Academic Publisher’s, Shanghai, China vol. 8, pp. 279-292.
16. Dearden, R. Friedman, N. Russell, S. (1998) Bayesian Q-learning”, AAAI- Proceedings.
17. Castronovo, M. Maes, F. Fonteneau, R. Ernst, D.(2012) “Learning Exploration/Exploitation Strategies for Single Trajectory Reinforcement Learning,” Workshop and Conference Proceedings, vol. 24, pp. 1–9.

18. Mignona, A. S. Rocha, R. L. A.(2016) An Adaptive Implementation of E-Greedy in Reinforcement Learning," Procedia Computer Science, vol. 109, pp. 1146–1151.
19. Alipourl, M. M. Raza, S. N. Balafar, M. A. (2017) A hybrid algorithm using a genetic algorithm and multiagent reinforcement learning heuristic to solve the traveling salesman problem,Neural Comput and Applic, vol. 30, pp. 2935–2951.
20. Afanasyeva, A. Buzdalov, M(2011) "Choosing best fitness function with reinforcement learning," International Conference on Machine Learning and Applications and Workshops, Honolulu, HI, USA, Dec. 18-21,2011 pp. 354 – 357.
21. Even-Dar, E. Mansour, Y. (2003)"Learning rates for Q-learning," Journal of Machine Learning Research, vol. 5, pp. 1-25.
22. Liu, D. Niu, D. Wang, H. Fan, L.(2014) Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm, Renewable Energy, vol. 62, pp. 592-597.
23. Santos, J. P. Q. Junior, F. C. L. Melo, R. M.M. J. D. Neto, A. D. D. (2009) A Parallel Hybrid Implementation Using Genetic Algorithm, GRASP and Reinforcement Learning, Proceedings of International Joint Conference on Neural Networks, Atlanta, GA, USA , June 14-19, 2009, pp. 2798-2803.
24. Liu, D. Niu, D. Wang, H. Fan, L.(2014) Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm, Renewable Energy, vol. 62, pp. 592-597.
25. Kaboudan, M.(2004) Wavelets in Forecasting, Research gate.
26. Alwadi, S.(2011) Selecting Wavelet Transforms Model in Forecasting Financial Time Series Data Based on ARIMA Model," Applied Mathematical Sciences, Vol. 5, pp. 315– 326.
27. Voronin, S. Partanen, J. (2013) Forecasting electricity price and demand using a hybrid approach based on wavelet transform, ARIMA and neural networks, International Journal of Energy Research, vol. 38, pp. 626-637, 2013.
28. Sudibyo, U. Eranisa, F. Rachmawanto, E. H. Setiadi, D. R. I. M. Sari, C. A.(2017) A Secure Image Watermarking using Chinese Remainder Theorem Based on Haar Wavelet Transform, Conf. on Information Tech., Computer, and Electrical Engineering (ICITACEE), pp. 208 – 212.
29. Alwakeel, M. Shaaban, Z.(2010) "Face Recognition Based on Haar Wavelet Transform and Principal Component Analysis via Levenberg-Marquardt Backpropagation Neural Network," European Journal of Scientific Research, Vol.42, pp. 25-31.
30. Swaidan, W. Hussin, A. (2014) "Haar wavelet operational matrix method for solving constrained nonlinear quadratic optimal control problem," American Institute of Physics, Selangor, Malaysia, Nov. 24–26.
31. Gurumoorthy, S. Muppalaneni, N. B Kumari, G. S. (2020) "EEG Signal Denoising using Haar Transform and Maximal Overlap Discrete Wavelet Transform (*MODWT*) for the finding of epilepsy," Intechopen.
32. Shaarawy S. Broemeling, L. (2007) "Bayesian inferences and forecasts with moving averages processes," Communications in Statistics - Theory and Methods, Vol. 13, p.p 1871-1888.
33. Vandewalle, N. Ausloosa, M. Boverouxb, Ph. (1999) "The moving averages demystified," Physica A: Statistical Mechanics and its Applications, vol. 269, pp. 170-176.
34. James, F. E. (2016) "Monthly Moving Averages: An Effective Investment Tool?," The Journal of Financial and Quantitative Analysis, vol. 3, pp. 315-326.
35. Holt, C. C. (2004)"Forecasting seasonal and trends by exponentially weighted moving averages," International Journal of Forecasting, vol. 20, pp. 5– 10.
36. Chandar, S. K. Sumathi, M. Sivanandam, S. N. (2016) " Prediction of Stock Market Price using Hybrid of Wavelet Transform and Artificial Neural," Indian Journal of Science and Technology, vol. 9, pp. 8-15, 2016.
37. http://www.eia.gov
38. Kwan, S.H. Mertens, T.M. (2020) "Market assessment of COVID–19", FRBSF Economic Lett, vol. 14 ,pp. 1–5.
39. Kulkarni, S. and Haidar, I. (2019) "Forecasting Model for Crude Oil Price Using Artificial Neural Networks and Commodity Futures Prices," IJCSIS vol. 2, pp. 1-8.