LITERATURE SURVEY

Date	10 September 2022
Project Name	Crude Oil Prediction
Maximum Marks	4 Marks

1. ABSTRACT:

The most important strategic resource on the planet, crude oil is the "key" commodity for the global economy. As a result, it has been challenging to anticipate since a variety of factors influence its price, making it difficult to predict. Crude oil's pricing is extremely unstable and variable. Numerous studies have lately been carried out to analyse the challenges of oil price forecasting and identify the best solutions. Anticipating its demands will be advantageous for our government, businesses, and investors. Long short-term memory, RNN(LSTMs) will be constructed as part of this research to estimate crude oil prices. In this paper, we propose an innovative analytical approach for forecasting the price of crude oil. Keywords: Economy, energy, gasoline, pricing, and crude oil.

2. LITERATURE SURVEY:

2.1.Application of Traditional and Statistical Econometric Models:

Academic academics are starting to use the usual statistical and econometric approaches among the various forecasting models created to anticipate the price of "black gold." Amano offers the first study on oil market forecasts(1987). To forecast the oil market, the author employed a small-scale econometric model. Huntington (1994) used an advanced econometric model to forecast the price ofoil in the 1980s. Gulen (1998) used co-integration analysis in a different study to forecast the price of WTI crude oil. Barone-Caddesi et al. (1998) proposed a semi-parametric approach based on the filtered historical simulation technique to predict the price of oil. Morana (2001) used a semi-parametric technique based on the GARCH features of the volatility of oil prices, which were studied by Barone-Caddesi et al (1998) suggested a semi-parametric approach based on the filtered historical simulation technique to forecast oil prices. Based on the GARCH properties of the oil price volatility, Morana (2001) employed a semi-parametric approach investigated by

Barone-Caddesi et al. (1998) to short-term Brent crude oil price forecast. In another work, Tang and Hammoudeh (2002) utilized a nonlinear regression to predict OPEC basket prices. Using OECD petroleum inventory levels and relative stock inventories, Ye et al. (2002, 2005) adopted a simple linear regression model for short-term monthlyprediction of WTI crude oil spot price. In a related study, Ye et al. (2006) included nonlinear variables such as low- and high-inventory variables to the linear forecasting model suggested by Ye et al. (2002, 2005) to predict short-run WTI crude oil prices.
Zamani (2004) used an econometrics forecasting model to anticipate the short-term quarterly WTI crude oil spot price using OECD stocks, non-OECD demand, and OPECsupply. Using error correction models, Lanza et al. (2005) looked at the pricing of products and crude oil. Sandusky (2006) used GARCH, TGARCH, AR, and BIGARCHstatistical models, among others, to forecast daily volatility in petroleum futures price returns. To predict oil demand, supply, and prices, Dees et al. (2007) created a linear model of the global oil market with a primary focus on OPEC behaviour. Murat and Tokat (2009) looked into the connection between futures and spot crude oil prices and used the random walk model to test if futures prices might predict changes in spot prices.

However, more recent research has used GARCH and several models from the GARCH family to forecast oil prices. For instance, the GARCH model was employed by Narayan and Narayan (2007) and Agnolucci (2009) to forecast spot and futures crude oil prices. In a related study, Mohammadi and Su (2010) investigated the crude oil price-predicting outcomes of various GARCH-type models. CGARCH, FIGARCH, and IGARCH modelswere suggested by Kang et al. (2009) to predict the volatility of crude oil markets.

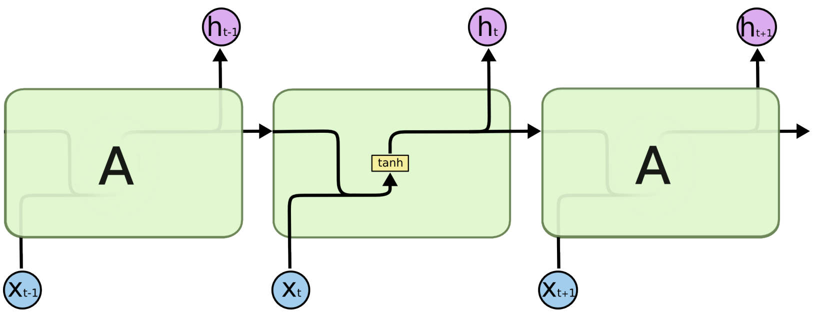
Wei et al. (2010) enhanced the work of Kang et al. (2009) towards the same goal by usinglinear and nonlinear GARCH-class models. As a result of the application of linear techniques, a sizable difference between the projected and real price of oil has been demonstrated. The most often utilised exogenous variables in these models for predicting oil prices are inventories, supply, and demand. The fact that supply and demand are relatively inelastic to price changes and that inventory adjustments can take time to materialise account for a considerable share of the difference between actual and predicted prices, especially in the near run (Hamilton, 2008). However, traditional statistical and economic techniques frequently only detect linear processes in data. data time series. (Weigend and Gershenfeld, 1994). However, the oil price behaviour is characterized by high nonlinearity and irregularity. Therefore, the mentioned models are not the appropriate choice to forecast the oil price.

2.2. Long short term memory(LSTM):

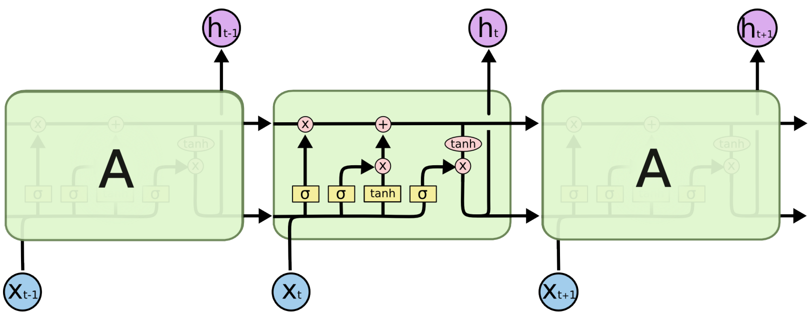
Long Short-Term Memory networks – usually just called “LSTMs” – are a special kind of RNN, capable of learning long-term dependencies. They were introduced by Hochreiter & Schmidhuber (1997) and were refined and popularized by many people in the following work.1 They work tremendously well on a large variety of problems and are now widely used.

LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods is practically their default behaviour, not something they struggle to learn!

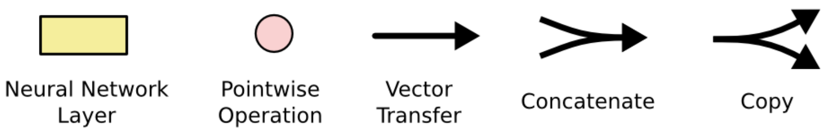
All recurrent neural networks have the form of a chain of repeating modules of neural networks. In standard RNNs, this repeating module will have a very simple structure, such as a single tanh layer.



The repeating module in a standard RNN contains a single layer.
LSTMs also have this chain-like structure, but the repeating module has a different structure. Instead of having a single neural network layer, there are four, interacting in a very special way.



The repeating module in an LSTM contains four interacting layers.
Don’t worry about the details of what’s going on. We’ll walk through the LSTM diagram step by step later. For now, let’s just try to get comfortable with the notation we’ll be using.



In the above diagram, each line carries an entire vector, from the output of one node to the inputs of others. The pink circles represent pointwise operations, like vector addition, while the yellow boxes are learned neural network layers. Lines merging denote concatenation, while a line forking denotes its content being copied and the copies going to different locations.

3. a.McCulloch & Pitts's (1943) neuron model

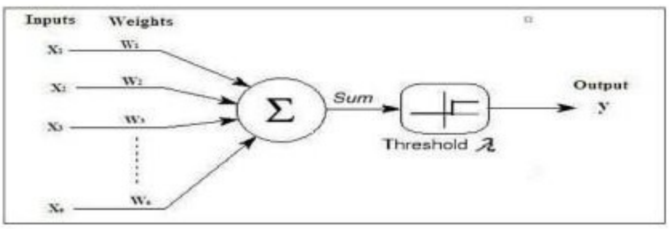
McCulloch & Pitts (1943) neuron model McCulloch and Pitts (1943) proposed thefirst artificial neuron also called the formal neuron. Mathematically, McCulloch wrote as follows:

$$y = f\left(\sum_{i=1}^{n} w_i x_i - \lambda\right)$$

Where 1 2 x , x , ..., n x represent the McCulloch- Pitts neuron inputs that are exclusivelybinary values (zeros or ones), 1 2 , ,..., w w wn are the connections‟ weights received by the neuron. f is the sign function, λ is the threshold and y is the output of McCulloch - Pitts neuron defined as:

$$f((x_1,\dots,x_n),(w_1,\dots,w_n)) = \begin{cases} 1, & \text{if } \sum_{i=1}^{n} w_i x_i \geq \lambda \quad (2) \\ 0, & \text{if } \sum_{i=1}^{n} w_i x_i < \lambda \quad (3) \end{cases}$$

Figure 2. Illustration of McCulloch & Pitts (1943) neuron



b) Multilayer perceptron model

Perceptron neural networks only have two layers and assume binary input-output values, which explains why the model can only handle linearly separable functions when hidden layers are absent. The delta rule, created in 1960 by Windrow and Hoff, involves adjusting the connection weights to reduce the difference between the desired and actual output value. The output value can therefore accept any value in place of 0 and 1. Minsky and Papert (1969) emphasised the importance of incorporating one or more hidden layers to identify the complex properties present in the inputs in their book. The multilayer perceptron net has traditionally been trained using the backpropagation learning method developed by Rumelhart et al. (described in greater detail in the following section) (1986). The multilayer perceptron is composed of a layer of input units, one or more hidden layers and an output layer (see Fig .4).

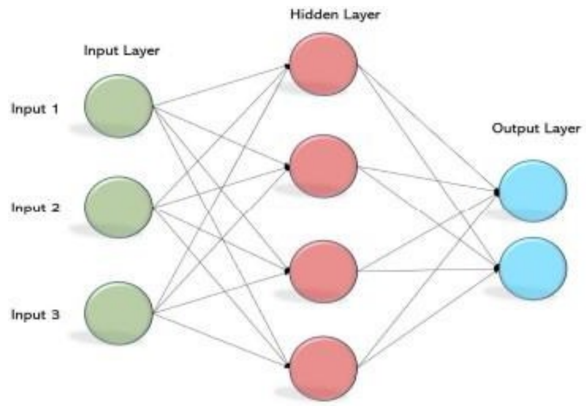


Figure:4

In this network system, the information propagates in a single direction „forward": the input units pass the information to the neurons in the first hidden layer, the outputs from the first hidden layer are subsequently

passed to the next layer, and so forth. Thus, the network output (for example, with onehidden layer) is:

$$y_k = h\left\{\sum_{j-1}^{J} w_2(j,k)\, g\left[\sum_{i=1}^{I} w_1(i,j)x_i + b_1(j)\right] + b_2(k)\right\}$$

Where: I x are the input variables of the network; I is the number of input variables; J is the total number of nodes in the hidden layer; K is the number of neurons in the output layer; g and h are, respectively, the transfer/activation function of the first and the second layer; w1 is the weights matrix of the hidden layer; w2 is the weights matrix of the outputlayer; 1 b and 2 b are the bias vectors of the hidden layer and the output layer, respectively. To note, at least one transfer function (see the next section for more description of the transfer function) of the hidden layer must be nonlinear (Hornik et al., 1989).

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