1. **Abstract**

As the most important strategic resource around the globe, crude oil is the “key” commodity for the world’s economy. Therefore, forecasting it has been challenging as many events influence its price, so it is very hard to forecast its prices. Crude oil price suffers from high volatility and fluctuations. Recently many studies occurred to discuss the problem of predicting oil prices and seeking access to the best results. Forecasting its needs will be helpful for our government, Companies, and Investors. This project involves creating an artificial neural network (ANN) to predict the price of crude oil. In this project, we propose a novel approach for crude oil price prediction based on artificial.

**Keywords**: Crude oil, economy, energy, fuel, price, Neural Networks.

1. **Literature Survey**

**2.1 Application of Traditional and Statistical Econometric Models:**

Among many different forecasting models that have been developed to predict the "black gold" price, the traditional statistical and econometric methods are the first ones to be applied by academic researchers. The first research about forecasting the oil market is proposed by Amano (1987). The author used a small-scale econometric model for oil market prediction. Huntington (1994) utilized a sophisticated econometric model for predicting oil prices in the 1980s. In another work, Gulen (1998) applied cointegration analysis to predict the WTI crude oil price. 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) for the short-term forecast of Brent crude oil price. 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 monthly prediction 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. Using OECD stocks, non-OECD demand, and OPEC supply, Zamani (2004) applied an econometrics forecasting methodology to short-term quarterly WTI crude oil spot price. Lanza et al. (2005) investigated crude oil and product prices by utilizing error correction models. Sandusky (2006) applied multiple univariate and multivariate statistical models such as GARCH, TGARCH, AR, and BIGARCH to the daily forecast of volatility in petroleum futures price returns. Slightly more recently, Dees et al. (2007) developed a linear model of the world oil market to predict oil demand, supply, and prices focusing mainly on OPEC behavior. Murat and Tokat (2009) investigated the relationship between futures and spot crude oil prices and therefore tested the ability of futures prices to forecast spot price movements using a random walk model. Cheong (2009) adopted ARCH models to forecast crude oil markets.

On the other hand, more recent studies have applied GARCH as well as different models of the GARCH family to predict oil prices. For example, Narayan and Narayan (2007) and Agnolucci (2009) used the GARCH model to forecast spot and futures crude oil prices. In related research, Mohammadi and Su (2010) compared the forecasting results of various GARCH-type models to predict the crude oil price. Kang et al. (2009) proposed CGARCH, FIGARCH, and IGARCH models to forecast the volatility of crude oil markets.

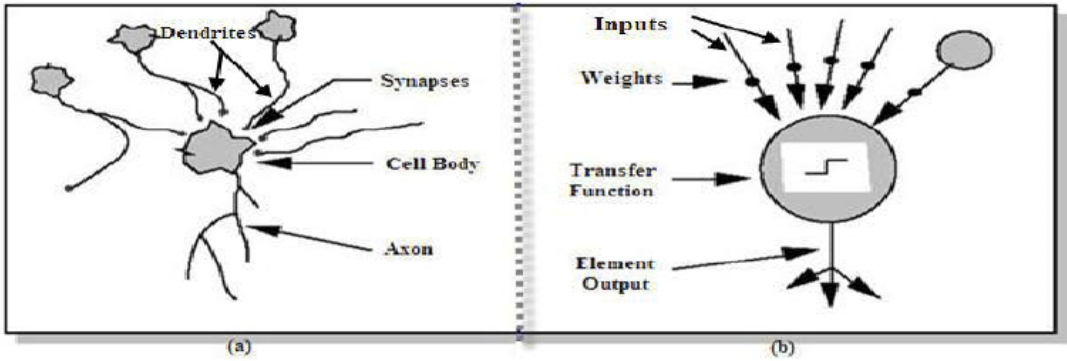
For the same purpose, Wei et al. (2010) extended the study of Kang et al. (2009) by applying linear and nonlinear GARCH-class models. As a result of the application of linear techniques, a significant error has been demonstrated between actual and predicted oil prices. Several exogenous variables have been employed with these models to predict oil prices; however; inventory, supply, and demand are the most used factors. Supply and demand are relatively inelastic to price changes, subsequently, an inventory adjustment can be slow to happen which explains the major part of the difference between real and forecasted prices, especially in the short run (Hamilton, 2008). On the other hand, traditional statistical and econometric techniques are usually able to capture only linear processes in data time series (Weigend and Gershenfeld, 1994). However, the oil price behavior is characterized by high nonlinearity and irregularity. Therefore, the mentioned models are not the appropriate choice to forecast the oil price.

**2.2 Artificial Neural Network (ANN):**

**2.2.1 Definition and Neuron Model Evolution**

**2.2.1.1 Definition**

ANN is an input-output mathematical model inspired by the human brain functioning by adopting the same mode of acquiring knowledge through the learning process. Fig. 1 summarizes an analogy between biological and artificial neurons.

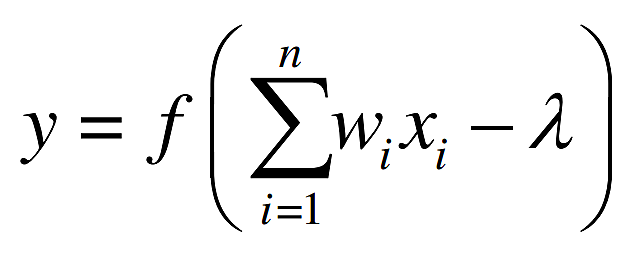


**Figure 1. The analogy between a biological neuron (a) and an artificial neuron (b)**

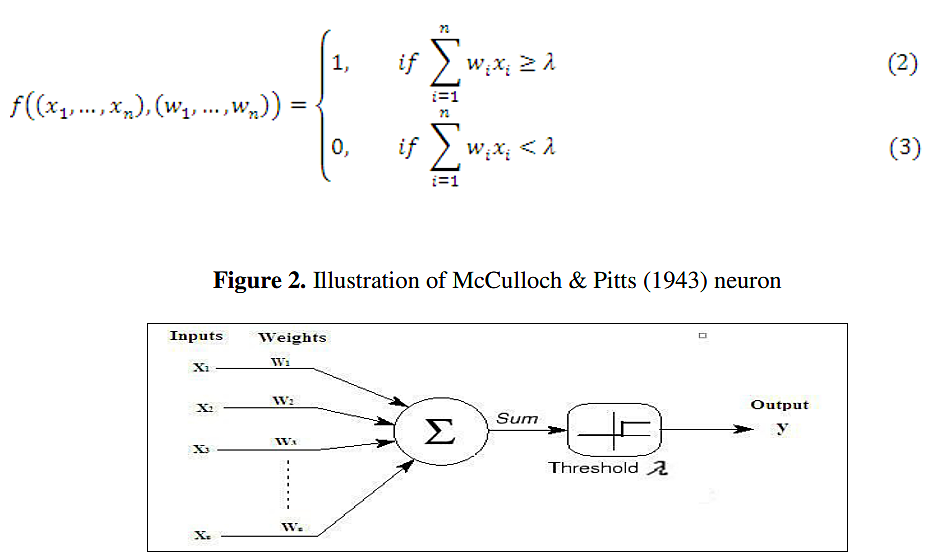
**2.2.1.2 Neuron Model Evolution**

**a) McCulloch & Pitts (1943) neuron model**

McCulloch & Pitts’s (1943) neuron model McCulloch and Pitts (1943) proposed the first artificial neuron also called the formal neuron. Mathematically, the McCulloch-Pitts neuron model can be written as follows:

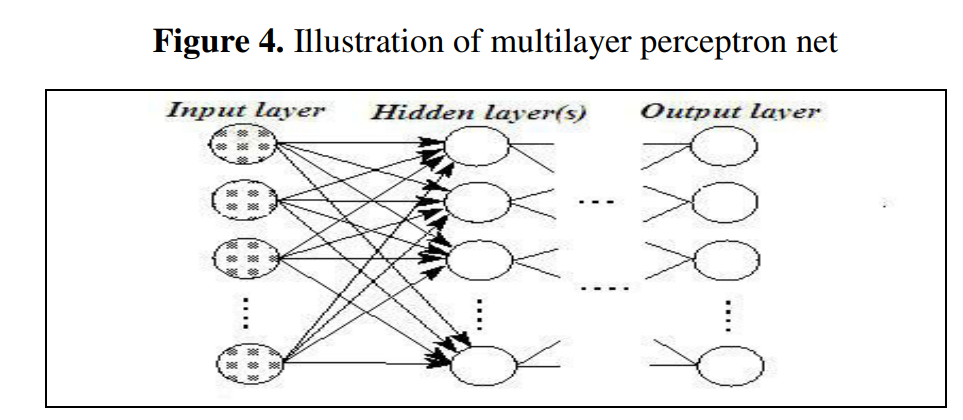


Where 1 2 x, x, ..., n x represent the McCulloch-Pitts neuron inputs that are exclusively binary values (zeros or ones), 1 2,..., w w we are the connections‟ weights received by the neuron. f is the sign function,  are the threshold and y is the output of McCulloch-Pitts neuron defined as:

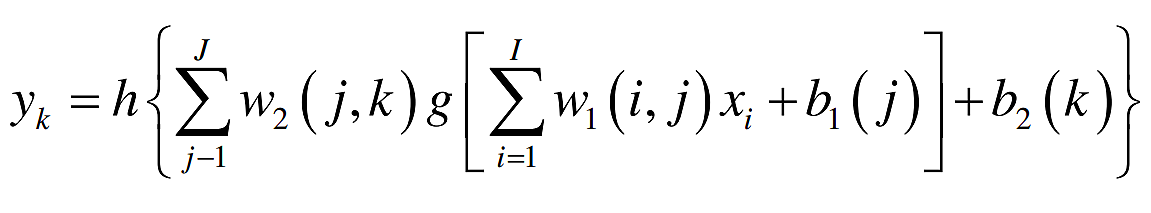


**b) Multilayer perceptron model**

Perceptron neural nets without hidden layers suppose only binary values of input-output as well as only two layers which explain the capability of the model to treat only the linearly separable functions. Windrow and Hoff (1960) introduce a learning rule called the delta rule consisting of modifying the connections‟ weights to reduce the difference between desired and actual output value. Therefore, the output value can take any value instead of 0 and 1. Minsky and Papert (1969) highlighted, in their book, the utility of adding one or more hidden layers to detect the complex features present in the inputs. The multilayer perceptron net was trained, traditionally, based on the backpropagation learning algorithm (detailed in the next section) developed by Rumelhart et al. (1986). The multilayer perceptron is composed of a layer of input units, one or more hidden layers, and an output layer (see Fig .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 one hidden layer) is :



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 output layer; 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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