

# Predicting the Price of Crude Oil and its Fluctuations Using Computational Econometrics: Deep Learning, LSTM, and Convolutional Neural Networks

Rayan H. Assaad\*♣ and Sara Fayek♠

♣New Jersey Institute of Technology, United States

♠Missouri University of Science and Technology, United States

Submitted: October 19, 2020 • Accepted: March 20, 2021

---

**ABSTRACT:** There has been a renewed interest in accurately forecasting the price of crude oil and its fluctuations. That said, this paper aims to study whether the price of crude oil in the United States (US) could be predicted using the stock prices of the top information technology companies. To this end, time-series data was collected and pre-processed as needed, and three architectures of computational neural networks were tested: deep neural networks, long-short term memory (LSTM) neural networks, and a combination of convolutional and LSTM neural networks. The findings suggest that LSTM networks are the best architectures to predict the crude oil price. The outcomes of this paper could potentially help in making the oil price prediction mechanism a more tractable task and in assisting decision-makers to improve macroeconomic policies, generate enhanced macroeconomic projections, and better assess macroeconomic risks.

---

**JEL classification:** A1, C1, C3, C5, C6, Q3.

**Keywords:** Crude Oil Price, Information Technology, Deep Learning, Long-Short Term Memory (LSTM), Convolutional Neural Networks, Stock Prices.

---

\*Corresponding Author. E-mail: rayan.hassane.assaad@njit.edu

## 1 Introduction

Crude oil is a naturally occurring unrefined petroleum product composed of hydrocarbon deposits and other organic materials, and it can be refined to produce usable products such as gasoline, diesel, and different forms of petrochemicals (Chen, 2020). Crude oil is considered one of the most important fuel sources and contributes to over a third of the world's energy consumption thus making the global oil industry a multitrillion sector (Corporate Finance Institute, 2020).

The surge in the crude oil price since 2002 has renewed interest in determining what variables affect the price of crude oil and has highlighted the importance of the ability to accurately predict the evolution of its price (Alquist and Kilian, 2010). Although there has been an increased interest in prediction capabilities (Assaad and El-Adaway, 2020), no previous study has tried to predict the price of crude oil based on the stock prices of the top information technology companies in the US. Therefore, this paper, through the use of machine learning predictive analytics, aims to study whether the price of crude oil in the United States (US) could be determined or predicted using the stock prices of the top information technology companies.

Machine learning techniques were chosen over other methods because they are considered to be superior on many levels such as accuracy, automation, speed, customizability, scalability (Jain, 2015; Assaad and El-adaway, 2020; Assaad and El-Adaway, 2021) as well as their flexibility and capabilities in handling multi-dimensional and multi-variety data in dynamic and uncertain environments (Gowri et al., 2019). Moreover, they require few assumptions to apply them (Coddling, 2013), they can generalize over a large degree of data variation (Amin and Al-Darwish, 2006) and they are able to discover patterns in data that exhibit significant unpredictable non-linearity (Kanevski et al., 2004; Assaad and El-adaway, 2020a). More precisely, in this paper, the authors employed deep neural networks (DNN), long-short term memory (LSTM) networks, and convolutional neural networks (CNN).

## 2 Theoretical Underpinnings and the Choice of the Information Technology Sector

This section aims to provide the theoretical underpinnings of the research performed in this paper as well as the reasons behind choosing the information technology sector.

Crude oil plays a critical role in the world economy since around two-thirds of the world's energy demands are met from crude oil, and it is also the world's largest and most actively traded commodity (Yu et al., 2008). Despite its importance, oil price prediction is considered to be an intractable task due to the complexity of the oil market mechanism (Jammazi and Aloui, 2012). Moreover, the prices of crude oil are generally believed to have a considerable impact on the overall US economy (Ewing and Thompson, 2007).

A considerable number of the previous studies have provided theoretical and empirical evidence of possible relationship(s) between the crude oil price and the stock prices. For instance, the reaction of stock markets to shocks in the oil price and the reasons behind such movements were examined by Jones and Kaul (1996). Sadorsky (1999) showed that fluctuations in the oil price could explain the forecast error variance of stock returns. Moreover, El-Sharif et al. (2005) offered additional background on previous findings on the relationship between oil prices and measures of stock market performance. Their study showed that there existed a specific link between fluctuations in the oil price and share values of oil and gas companies. The theoretical underpinning for the existence of possible relationships between the crude oil prices and the stock prices of companies in different sectors or industries was best summarized and described by Yun and Yoon (2019): *The price of crude oil has a non-negligible influence on many industries and enterprises. Based on our literature review, we find that the crude oil price has an influence on the stock market in the following three ways. First, the crude oil is an important raw material in the economic activities, and a change in crude oil price will lead to changes in production cost and expected cash flows. According to the Discounted Cash Flow (DCF) model, the expected cash flows of an enterprise are an important factor influencing its value. Therefore, the change in crude oil price will have an influence on the stock market price through the cash flows (Huang et al., 1996; Basher and Sadorsky, 2006). Second, in the DCF model, another factor influencing the enterprise value is the discount rate. The rise of crude oil price triggers a price run-up, and then, leads to inflation. If the central bank curbs inflation by raising the interest rate, the higher interest rate will lead to an increase in the discount rate, which then has an adverse effect on the stock market price of enterprises (Huang et al., 1996; Degiannakis et al., 2017). Third, the rise of crude oil price will trigger a rise in commodity prices, leading to a reduction in market demand reduction, and then, a reduction in the enterprise production scale (Edelstein and Kilian, 2009; Filis et al., 2011).*

In relation to that, this paper focuses on the stock prices of the top companies in the information technology sector which comprises companies that produce software, hardware, or semiconductor equipment as well as firms that offer internet or related services (Miller, 2019). The information technology sector was chosen for many reasons such as (1) the sector being central to the digital pivot for developed and developing countries (Henry-Nickie et al., 2019); (2) the sector being central to the nation's economy, safety, security, and public health (Cybersecurity and Infrastructure Security Agency, 2014); (3) the fact that analyzing aggregate growth trends in the information technology sector could provide a useful picture of the sub-industries that are critical to its growth and the broader economy (Henry-Nickie et al., 2019); and (4) the fact that the proliferation of digital technologies will continue to bring unprecedented structural changes to the US economy, cementing the information technology sector as a leading source of growth and employment (Henry-Nickie et al., 2019).

### 3 Literature Review

This section aims to provide a review of the existing literature related to the paper's specific topic on the prediction of the crude oil price and the use of artificial neural networks or other artificial intelligence algorithms. There were a number of researchers that showed the ability of machine learning techniques in studying the fluctuations in the price of crude oil. In relation to that, Xie et al. (2006) proposed a new method for crude oil price forecasting based on a support vector machine model for time series forecasting involving data sampling, sample preprocessing, training and learning, and out-of-sample forecasting. Liu et al. (2007) proposed a new oil price forecasting model based on a fuzzy neural network, which combines a radial basis function neural network, Markov chain-based semi parametric model, and wavelet analysis. Yu et al. (2008) proposed an empirical mode decomposition-based neural network ensemble learning paradigm to forecast the world crude oil spot price. Kulkarni and Haidar (2009) presented a model based on a multilayer feedforward neural network to forecast crude oil spot price direction in the short-term (up to three days ahead). Mingming and Jinliang (2012) constructed a multiple wavelet recurrent neural network simulation model, in which trend and random components of crude oil and gold prices were considered. Jammazi and Aloui (2012) combined the dynamic properties of the multilayer backpropagation neural network and the Harr à trous wavelet decomposition to predict the crude oil price. Wang et al. (2012) introduced and applied a jump stochastic time effective neural network model to forecast the fluctuations of the time series for the crude oil prices and the stock indices in China. Azadeh et al. (2012) presented a flexible algorithm based on artificial neural network and fuzzy regression to cope with optimum long-term oil price forecasting in noisy, uncertain, and complex environments. Shabri and Samsudin (2014) proposed a new method based on integrating discrete wavelet transform and artificial neural networks model for daily crude oil price forecasting. Chiroma et al. (2015) proposed an alternative approach based on a genetic algorithm and neural network for the prediction of the West Texas Intermediate crude oil price. Wang and Wang (2016) established a new neural network architecture that combines multilayer perception and Elman recurrent neural networks with stochastic time effective function to improve the forecasting accuracy of crude oil price fluctuations. Mahdiani and Khamehchi (2016) used a modified neural network model, by having a genetic algorithm optimize its parameters, to predict the future price of crude oil. Zhao et al. (2017) proposed a deep learning ensemble approach to model the nonlinear and complex relationships of oil price with its influencing factors. Huang and Wang (2018) proposed a method that combines wavelet neural network with the random time effective function to improve the prediction accuracy of crude oil price fluctuations. Li et al. (2019) suggested a new and novel crude oil price forecasting method based on online media text mining, with the aim of capturing the more immediate market antecedents of price fluctuations. More recently, Gupta and Nigam (2020) proposed a contemporary and innovative method of predicting crude oil prices using artificial neural networks to continuously capture the

unstable pattern of the crude oil prices. Zou et al. (2020) presented a variational mode, decomposition-convolutional neural network model, to forecast the risk movement in the major crude oil markets.

As presented above, many previous research efforts have been directed to study and predict the crude oil price and its fluctuations using different artificial neural network architectures and multiple machine learning approaches. However, none of the previous studies have been directed to study whether the price of crude oil in the US could be determined or predicted using the stock prices of the top information technology companies. Therefore, this paper aims to address this critical research need and knowledge gap through the use of machine learning predictive analytics.

## 4 Methodology

This section presents the methodology employed in this study. The subsequent subsections address the details of data collection, data preprocessing, data division, data processing, and model performance evaluation.

### 4.1 Data Collection and Descriptive Statistics

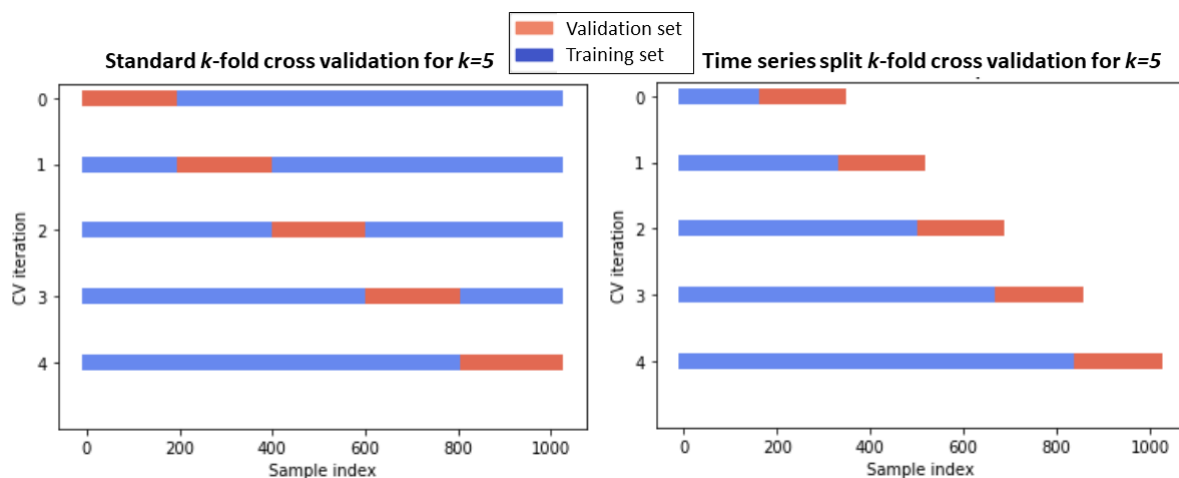
Since many information technology companies are located in the US, it would be unreasonable to include all of them in this research. This paper focuses on the top 20 publicly traded companies, which are: Apple Inc. (APPL), Microsoft Corp. (MSFT), Visa Inc. (V), Mastercard Inc. (MA), Intel Corp. (INTC), Cisco Systems Inc. (CSCO), Adobe Inc. (ADBE), NVIDIA Corp. (NVDA), Salesforce.com Inc. (CRM), Alphabet Inc. (GOOG), International Business Machines Corp. (IBM), Hon Hai Precision Industry Co. (HNHPF), Tencent Holdings Lim. (TCEHY), Oracle Corp. (ORCL), Taiwan Semiconductor Manufacturing Co. (TSM), AT&T Inc. (T), Verizon Communications (VZ), HP Inc. (HPQ), Facebook Inc. (FB), and Dell Technologies (DELL). They were chosen based on the following criteria: (1) the stock prices of the companies being traded in the US rather than in other countries; (2) the companies themselves being traded publicly rather than privately (so that the stock prices are available to collect); (3) the companies representing a significant proportion of the whole information technology sector in the US; and (4) the time series being long enough (more than 10 years, i.e. at least since 2010). The daily closing stock prices of these companies were collected from Yahoo! Finance. The daily spot price of crude oil in the US, on the other hand, was collected from the US Energy Information Administration. The collected data is time-series data with a time step of one day. Descriptive statistics including mean, standard deviation, maximum, minimum, first quartile, second quartile, and third quartile are reported for the collected dataset of all variables.

## 4.2 Data Division

The classical cross-validation methods, such as  $k$ -fold cross-validation, assume that the samples are independent and identically distributed; which is not the case for time series data. Therefore developing computational machine learning models for time series data needs specific care (Monnier, 2018). The reason behind this is that time-series data is characterized by the dependence of data observations that are close in time. To this end, using the standard  $k$ -fold cross-validation method for time series data would lead to an unreasonable correlation between training and testing instance; and, consequently, to poor estimates of generalization error (Scikit-learn, 2020).

A revised version of the standard  $k$ -fold cross validation exists to deal with time-series data in which the dataset is evaluated on the ‘future’ observations rather than ‘random’ observations. This revised version is known as the time series split where the training set is divided at each iteration in a way that the validation set is always ahead of the training split (Packt, 2019). In order to illustrate this idea better, Figure 1 shows the difference between the classical  $k$ -fold cross-validation technique and the time series split  $k$ -fold cross-validation method used for time series data.

Figure 1: Classical  $k$ -fold cross validation vs. time series split cross validation



Source: Packt (2019).

Based on the above, the data division protocol used in this paper is as follows: (1) divide the entire 2010-2019 data to training set 2010-2017 inclusive (which is around 80%) and to a holdout set 2018-2019 inclusive (which is around 20%) of the data, therefore the forecasting horizon is the two year period from the start of 2018 till the end of 2019; (2) use time series split 5-fold cross-validation on the training set (as shown in Figure 1); (3) evaluate the performance of the model on each one of the 5 validation splits for each iteration; (4) select the computational model’s hyperparameters based on the lowest validation error; (5) evaluate the final performance of the developed model on the unseen holdout set. The details on the data processing steps are present in the next subsection.

### 4.3 Data Preprocessing

Before developing any model, data should be appropriately pre-processed. In order to do so, the data was cleaned by removing the days on which no stock prices were recorded for the information technology companies considered in this research. In addition, a 10-year study period between 2010 and 2019 was used to ensure that enough data had been processed to develop the model. As a result, any information technology company which was not publicly traded before 2010, was disregarded from the analysis (these firms include FB and DELL). In addition, since the variables considered in this paper possess varying magnitudes, the collected time series data was scaled to a range of  $[0, 1]$  using the min-max scaling method:

$$z = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

Where  $z$  is the scaled version of the unscaled variable  $x$ .

### 4.4 Data Processing

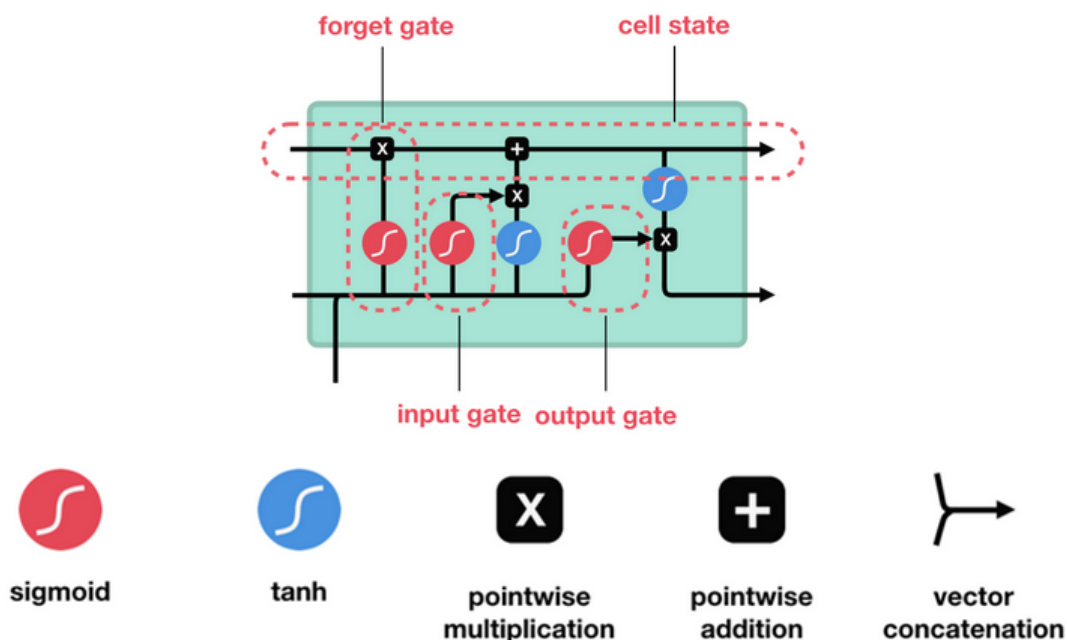
After data pre-processing, three architectures of neural networks were used in order to process the data including DNN, LSTM networks, and a combination of CNN and LSTM. These architectures were chosen because they are capable of handling time series data.

DNNs are multi-layer feedforward neural networks with more than three layers including input and output layers (Nicholson, 2019). DNNs are generally nonlinear mathematical learning algorithms that attempt to imitate some of the workings of the human brain (Sarzaeim et al., 2017). In fact, DNNs are considered one of the most common supervised learning techniques that can identify or learn the relationship or pattern between output variables and input variables (Dawood et al., 2018), and they are a processing system formed from densely interconnected adaptive elements; called nodes or neurons (Assaad and El-Adaway, 2020). The structure of a typical DNN includes individual weights and biases for each neuron in the network, a transfer/activation function that determines the shape of the generated outputs, and learning methods or algorithms that update the individual parameters of each neuron (Mishra et al., 2017). Different combinations of hyperparameters for DNN were tuned in this paper in order to select the combination with the least validation error. The following six main different parameters were explored for all artificial neural network architectures: the number of hidden layers, the number of neurons in each hidden layer, the learning rate, the momentum, the batch size, and the number of epochs. In relation to that, the grid search method was used to find the optimal or best combination of parameters. Due to the length restrictions of this paper, only the results for the best combination of hyperparameters are reported.

Compared to other neural network architecture, LSTMs are able to process entire sequences of data as well as single data points; thus, LSTMs are most commonly used for temporal and time-series data (Jang et al., 2020; Gers et al., 2002). In fact, LSTMs are

considered a specific type of recurrent neural network that is capable of learning long-term temporal dynamics while avoiding the vanishing and exploding gradients problems that classical recurrent neural networks might be subject to (Jang et al., 2020). An LSTM unit comprises: (1) a cell, (2) an input gate, (3) an output gate, and (4) a forget rate as shown in Figure 2. The LSTM cell remembers values over time intervals while the gates regulate the flow of information. Different combinations of hyperparameters for LSTM were tuned in this paper to select the combination with the least validation error. These hyperparameters are: the number of LSTM layers, the number of cells/neurons, the learning rate, the momentum, the batch size, and the number of epochs. Due to the length restrictions of this paper, only the best combination of hyperparameters with the least validation error is reported.

Figure 2: The structure of a standard LSTM neural network



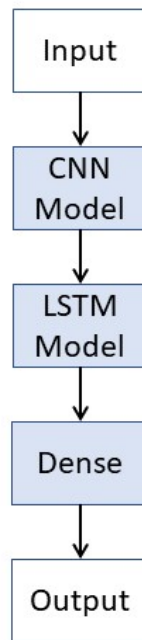
Source: Nguyen (2018).

The third neural network architecture used in this paper is a combination of CNN and LSTM which is referred to as ‘CNN-LSTM’. The goal behind introducing CNN into LSTM is the CNN’s capabilities in extracting important features in the data using different filters. The CNN and LSTM are two different modules that are aggregated together in the following way. The CNN is a standard convolutional layer that acts as a spatial-temporal feature extractor with the generated output being multiplied by the LSTM cell that is used to learn temporal features. In other words, CNN-LSTM architecture uses CNN as a front end (Brownlee, 2017). CNN-LSTM networks are *a class of models that are both spatially and temporally deep and sit at the boundary of Computer Vision and Natural Language Processing. These models have enormous potential and are being increasingly used for many sophisticated tasks* (Pardeshi, 2019). The general structure



of a CNN-LSTM is shown in Figure 3. Different combinations of hyperparameters for the CNN-LSTM model were tuned in this paper in order to select the combination with the least validation error. These hyperparameters are: the number of filters, the kernel size, the strides, the padding, the number of LSTM layers, the number of cells/neurons, the learning rate, the momentum, the batch size, and the number of epochs. Again, the authors only present the best combination of hyperparameters with the least validation error.

Figure 3: The structure of a CNN-LSTM neural network



Source: Brownlee (2017).

#### 4.5 Model Evaluation

All developed models were evaluated on the unseen holdout/testing set. Different prediction evaluation metrics were used in this research including the mean absolute percentage error (MAPE), the mean error (ME), the mean absolute error (MAE), the mean percentage error (MPE), the root mean square error (RMSE), and the correlation coefficient between the actual and predicted crude oil price. The equations for the different evaluation metrics are shown in Equations 2, 3, 4, 5 and 6. It is worth mentioning that the predictive performance of the chosen methods is assessed for the considered dependent variable (Crude Oil Price) in specific rather than for their predictive performance in general.

$$MAPE = \frac{100}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (2)$$

$$MPE = \frac{100}{n} \sum_{t=1}^n \frac{y_t - \hat{y}_t}{y_t} \quad (3)$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| \quad (4)$$

$$ME = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t) \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (6)$$

Where  $y_t$  is the actual value of the price of crude oil at time  $t$ , and  $\hat{y}_t$  is the predicted value.

Furthermore, the statistical test (Diebold and Mariano, 1995), with modification suggested by Harvey et al. (1997), was used with a significance level of 0.05 to statistically identify forecast accuracy equivalence for 2 sets of predictions. The null hypothesis of the Diebold-Mariano test is that the two forecasts have the same accuracy while the alternative hypothesis is that the two forecasts have different levels of accuracy; thus, one of them has superior predictive ability.

## 5 Results and Analysis

This section aims to present and analyze the results for the DNN, LSTM, and CNN-LSTM.

### 5.1 Descriptive Statistics

Table 1 shows the descriptive statistics for the collected data. As presented in Table 1, the variables possess different magnitudes. The collected data were scaled using the min-max method before being processed as detailed in the Methodology section.

### 5.2 Neural Network Architectures

Different combinations of hyperparameters were used for each of the three neural network architectures considered in this paper. The best parameters for the DNN are: 2 hidden layers, 10 neurons in each hidden layer, the learning rate of 0.01, the momentum of 0.9, the batch size of 72, and 1000 epochs. The best parameters for the CNN-LSTM are: 32 filters, kernel size of 5, strides of 1, causal padding, 2 LSTM layers, 32 neurons/cells, the learning rate of 0.001, the momentum of 0.9, the batch size of 72, and 1000 epochs. The

Table 1: Descriptive statistics for the collected data

Variable	Mean	Std	Min	25%	50%	75%	Max
Crude Oil Price	72.46	21.95	26.19	52.33	71.42	93.54	113.39
HPQ	13.43	4.83	3.93	9.77	12.84	17.00	25.13
IBM	132.61	16.87	88.70	125.17	134.94	144.98	165.51
INTC	28.84	11.99	13.20	18.57	27.07	33.97	59.79
AAPL	103.71	57.50	23.82	56.96	91.89	145.29	292.95
MSFT	52.26	35.08	18.23	24.33	40.02	67.46	158.53
V	69.23	47.63	13.72	27.15	62.20	93.71	189.12
MA	96.86	72.37	16.52	38.48	81.57	121.53	299.88
CSCO	25.46	11.42	10.61	16.80	21.94	29.92	56.66
ADBE	104.29	84.90	22.69	34.24	72.88	143.38	331.20
NVDA	69.99	80.53	8.17	13.72	19.80	142.25	287.77
CRM	71.80	41.69	15.52	37.14	61.22	89.56	166.95
GOOG	643.27	325.78	217.22	315.75	561.51	928.87	1361.17
HNHPF	4.41	0.97	2.38	3.73	4.35	4.87	7.59
TCEHY	20.74	16.24	3.13	5.81	16.42	35.01	60.66
ORCL	36.17	9.49	18.81	28.49	36.25	43.30	59.10
VZ	37.31	10.73	15.81	30.30	37.76	43.82	60.78
TSM	21.33	11.93	6.60	11.29	17.89	32.20	58.26
T	25.71	5.90	13.95	22.46	25.58	30.48	38.43

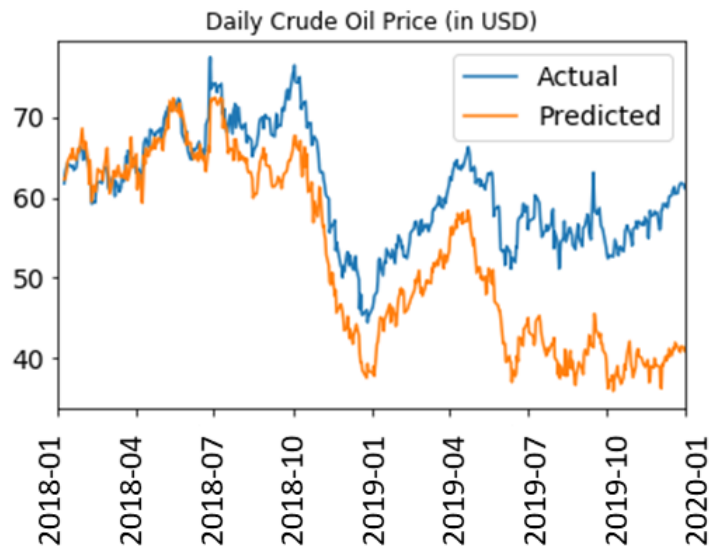
Source: Authors' calculation.

best parameters for the LSTM are: 1 LSTM layer, the learning rate of 0.1, the momentum of 0.9, the batch size of 72, 50 neurons/cells, and 1000 epochs.

The actual vs. predicted oil price using the three neural network models is presented in Figures 4, 5 and 6. The prediction evaluation metrics for the three neural network architectures are shown in Table 2. As mentioned in the Methodology section, the Diebold-Mariano test was implemented in order to determine whether forecasts were statistically significantly different between the multiple considered model architectures. The results of the Diebold-Mariano test are presented in Table 3. All  $p$ -values are less than the significance level of 0.05 which reflects strong evidence against the null hypothesis. Thus, it could be concluded that there are statistically significant differences between the prediction accuracies of the three considered neural network architectures. The results presented in Tables 2 and 3 suggest that the LSTM is the best neural network architecture.

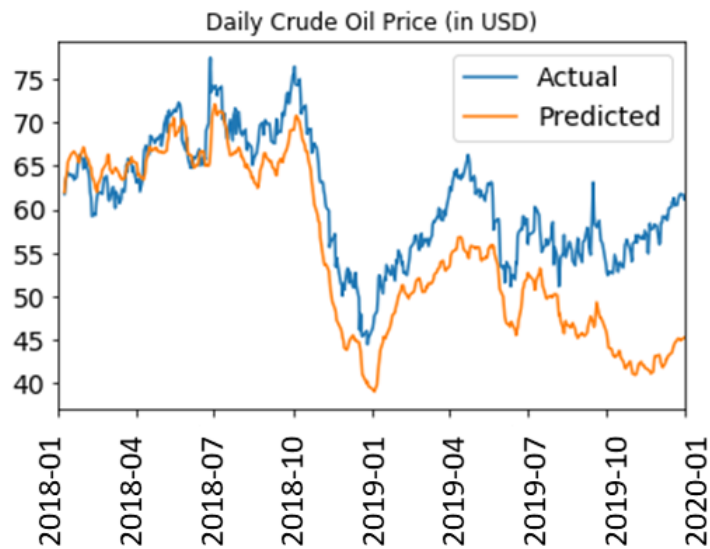
Finally, a naïve forecast model was developed, assessed, and statistically significantly compared with the best artificial neural network architecture (i.e. LSTM). The purposes were to examine whether more complicated methods (i.e. LSTM) could be beneficial

Figure 4: Results on the unseen holdout set using DNN



Source: Authors' calculation.

Figure 5: Results on the unseen holdout set using CNN-LSTM



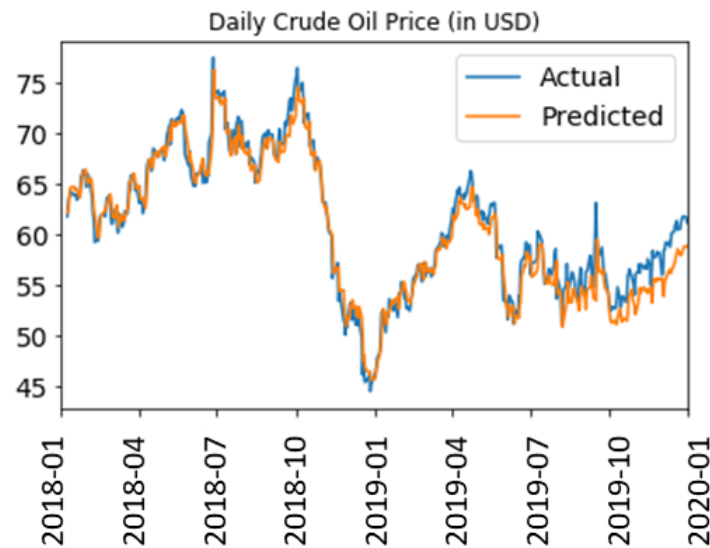
Source: Authors' calculation.

Table 2: Prediction evaluation metrics

Neural Network Architecture	MAPE	ME	MAE	MPE	RMSE	Correlation
DNN	14.32	-8.02	8.33	-13.83	10.22	0.87
CNN-LSTM	10.21	-5.48	6.00	-9.38	7.33	0.88
LSTM	2.09	-0.60	1.25	-0.97	1.64	0.97

Source: Authors' calculation.

Figure 6: Results on the unseen holdout set using LSTM



Source: Authors' calculation.

Table 3: Results for the Diebold-Mariano test

Combination of Neural Network Architectures	Diebold-Mariano (DM) Statistic	<i>P</i> -value
DNN and LSTM	19.80	1.16e-64
DNN and CNN-LSTM	16.38	1.70e-48
LSTM and CNN-LSTM	-16.81	1.73e-50

Source: Authors' calculation.

and to compare the predictive ability of models proposed in this paper with other simple benchmark methods (i.e. naïve forecast). The results obtained for the comparison between the naïve forecast and the LSTM model are shown in Table 4. They suggest that the LSTM model heavily outperforms the naïve forecast model. Nevertheless, to statistically examine such differences, the Diebold-Mariano test was implemented. The obtained DM statistic is -18.85 and the obtained *p*-value is 3.93e-60. Since the *p*-value is less than the significance level of 0.05, this reflects strong evidence against the null hypothesis. Therefore, it could be concluded that there are statistically significant differences between the prediction accuracies of the LSTM model and the naïve forecast model which suggests that the LSTM model is better than the simpler naïve forecast benchmark model; hence, the LSTM brings value.

Table 4: Prediction evaluation metrics

Model	MAPE	ME	MAE	MPE	RMSE	Correlation
Naïve forecast	9.55	0.38	5.71	1.87	6.74	-2.05e-16
LSTM	2.09	-0.60	1.25	-0.97	1.64	0.97

Source: Authors' calculation.

## 6 Conclusion and Future Work

This paper developed computational neural network models to predict the price of crude oil in the US based on the stock prices of the top information technology companies in the US. Three architectures were investigated in this research: DNN, CNN-LSTM, and LSTM. The findings of the paper suggest that the crude oil price could be predicted based on the stock prices of top information technology companies in the US. The findings of the paper also suggest that LSTM is the best neural network architecture that is able to predict the price of crude oil in an accurate way with a MAPE of 2.09%. This obtained MAPE is considered to be an acceptable range for the error since it is less than 10% (Fan et al., 2010; Assaad and El-adaway, 2020b).

The findings of this paper might potentially help in making the oil price prediction mechanism a more tractable task, which was usually not possible due to the intrinsic complexity of the oil market mechanism (Jammazi and Aloui, 2012). In fact, the gasoline and oil prices are considered to possess a chaotic behavior due to their high and unexpected volatility (Assaad and El-adaway, 2020b). Also, the crude oil price has been part of the decision-making process for development and production in industries, as well as government short- and long-term planning, export policy, and national reserves (Chiroma et al., 2015). That said, the outcomes of this paper equip decision-makers with a robust model which is able to predict the price of crude oil in an accurate way as well as help them understand the fluctuations in the crude oil price in the US better. It is important for decision-makers to predict the price of oil because such a commodity plays an important role in the global economy where unexpected large and persistent fluctuations in its price are detrimental to the welfare of economies. In fact, more accurate predictions of the price of oil have the potential of enhancing forecast accuracy for a wide range of macroeconomic outcomes, improving macroeconomic policy, generating macroeconomic projections, and assessing macroeconomic risks (Alquist et al., 2013). Ultimately, equipping decision-makers with effective predictive tools is very crucial and important (Assaad and El-adaway, 2020, 2021). Future work could include the use of advanced techniques such as optimization and photogrammetry (Fayek et al., 2020b,a, 2021) in the oil industry to study multiple aspects and characteristics.

## References

- Alquist, R. and Kilian, L. (2010). What Do We Learn From the Price of Crude Oil Futures? *Journal of Applied Econometrics*, 25(4):539–573.
- Alquist, R., Kilian, L., and Vigfusson, R. J. (2013). Forecasting the Price of Oil. In *Handbook of Economic Forecasting, Vol. 2*, pages 427–507. Elsevier.
- Amin, A. and Al-Darwish, N. (2006). Structural Description to Recognizing Hand-printed

- Arabic Characters Using Decision Tree Learning Techniques. *International Journal of Computers and Applications*, 28(2):129–134.
- Assaad, R., Dagli, C., and El-adaway, I. H. (2020a). A System-of-Systems Model to Simulate the Complex Emergent Behavior of Vehicle Traffic on an Urban Transportation Infrastructure Network. *Procedia Computer Science*, 168:139–146.
- Assaad, R. and El-Adaway, I. (2020). Forecasting and Modeling Bridge Deterioration Using Data Mining Analytics. In *Construction Research Congress 2020: Computer Applications*, pages 125–134. Reston, VA: American Society of Civil Engineers.
- Assaad, R. and El-adaway, I. H. (2020). Bridge Infrastructure Asset Management System: Comparative Computational Machine Learning Approach for Evaluating and Predicting Deck Deterioration Conditions. *Journal of Infrastructure Systems*, 26(3):04020032.
- Assaad, R. and El-Adaway, I. H. (2020). Enhancing the Knowledge of Construction Business Failure: A Social Network Analysis Approach. *Journal of Construction Engineering and Management*, 146(6):04020052.
- Assaad, R. and El-adaway, I. H. (2020a). Evaluation and Prediction of the Hazard Potential Level of Dam Infrastructures Using Computational Artificial Intelligence Algorithms. *Journal of Management in Engineering*, 36(5):04020051.
- Assaad, R. and El-adaway, I. H. (2020b). Impact of Dynamic Workforce and Workplace Variables on the Productivity of the Construction Industry: New Gross Construction Productivity Indicator. *Journal of Management in Engineering*, 37(1):04020092.
- Assaad, R. and El-Adaway, I. H. (2021). Determining Critical Combinations of Safety Fatality Causes Using Spectral Clustering and Computational Data Mining Algorithms. *Journal of Construction Engineering and Management*, 147(5):04021035.
- Assaad, R. and El-adaway, I. H. (2021). Guidelines for Responding to COVID-19 Pandemic: Best Practices, Impacts, and Future Research Directions. *Journal of Management in Engineering*, 37(3):06021001.
- Assaad, R., El-Adaway, I. H., and Abotaleb, I. S. (2020b). Predicting Project Performance in the Construction Industry. *Journal of Construction Engineering and Management*, 146(5):04020030.
- Azadeh, A., Moghaddam, M., Khakzad, M., and Ebrahimipour, V. (2012). A Flexible Neural Network-Fuzzy Mathematical Programming Algorithm for Improvement of Oil Price Estimation and Forecasting. *Computers and Industrial Engineering*, 62(2):421–430.

- Basher, S. A. and Sadorsky, P. (2006). Oil Price Risk and Emerging Stock Markets. *Global Finance Journal*, 17(2):224–251.
- Brownlee, J. (2017). CNN Long Short-Term Memory Network. <https://machinelearningmastery.com/cnn-long-short-term-memory-networks/>.
- Chen, J. (2020). Crude Oil. <https://www.investopedia.com/terms/c/crude-oil.asp>.
- Chiroma, H., Abdulkareem, S., and Herawan, T. (2015). Evolutionary Neural Network Model for West Texas Intermediate Crude Oil Price Prediction. *Applied Energy*, 142:266–273.
- Codding, P. W., editor (2013). *Structure-Based Drug Design: Experimental and Computational Approaches*. Springer Science+Business Media.
- Corporate Finance Institute (2020). Crude Oil Overview. <https://corporatefinanceinstitute.com/resources/knowledge/economics/crude-oil-overview/>.
- Cybersecurity and Infrastructure Security Agency (2014). Information Technology Sector. <https://www.cisa.gov/information-technology-sector>.
- Dawood, T., Zhu, Z., and Zayed, T. (2018). Computer Vision-Based Model for Moisture Marks Detection and Recognition in Subway Networks. *Journal of Computing in Civil Engineering*, 32(2):04017079.
- Degiannakis, S., Filis, G., and Arora, V. (2017). Oil Prices and Stock Markets. *Independent Statistics and Analysis, US Energy Information Administration, Washington, DC, 20585*, 20585.
- Diebold, F. X. and Mariano, R. S. (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics*, 13(3):253–264.
- Edelstein, P. and Kilian, L. (2009). How Sensitive Are Consumer Expenditures to Retail Energy Prices? *Journal of Monetary Economics*, 56(6):766–779.
- El-Sharif, I., Brown, D., Burton, B., Nixon, B., and Russell, A. (2005). Evidence on the Nature and Extent of the Relationship Between Oil Prices and Equity Values in the UK. *Energy Economics*, 27(6):819–830.
- Ewing, B. T. and Thompson, M. A. (2007). Dynamic Cyclical Comovements of Oil Prices With Industrial Production, Consumer Prices, Unemployment and Stock Prices. *Energy Policy*, 35(11):5535–5540.
- Fan, R. Y., Ng, S. T., and Wong, J. M. (2010). Reliability of the Box–Jenkins Model for Forecasting Construction Demand Covering Times of Economic Austerity. *Construction Management and Economics*, 28(3):241–254.



- Fayek, S., Xia, X., Li, L., and Zhang, X. (2020a). Photogrammetry-Based Method to Determine the Absolute Volume of Soil Specimen During Triaxial Testing. *Transportation Research Record*, 2674(8):206–218.
- Fayek, S., Xia, X., and Zhang, X. (2020b). A Least Square Optimization Approach for Determining the Soil Boundary and Absolute Volume of Unsaturated Soils. In *Geo-Congress 2020: Geo-Systems, Sustainability, Geoenvironmental Engineering, and Unsaturated Soil Mechanics*, pages 394–401. Reston, VA: American Society of Civil Engineers.
- Fayek, S., Xia, X., and Zhang, X. (2021). Validation of Least Square Optimization Method for Determining the Absolute Volume of Unsaturated Soils. In *4th International Conference on Transportation Geotechnics (ICTG)*. Reston, VA: American Society of Civil Engineers.
- Filis, G., Degiannakis, S., and Floros, C. (2011). Dynamic Correlation Between Stock Market and Oil Prices: The Case of Oil-Importing and Oil-Exporting Countries. *International Review of Financial Analysis*, 20(3):152–164.
- Gers, F. A., Eck, D., and Schmidhuber, J. (2002). Applying LSTM to Time Series Predictable Through Time-Window Approaches. In *Neural Nets WIRN Vietri-01*, pages 193–200. Springer, London.
- Gowri, S. G., Devi, R., and Sethuraman, K. (2019). Machine Learning. *International Journal of Research and Analytical Reviews*.
- Gupta, N. and Nigam, S. (2020). Crude Oil Price Prediction Using Artificial Neural Network. *Procedia Computer Science*, 170:642–647.
- Harvey, D., Leybourne, S., and Newbold, P. (1997). Testing the Equality of Prediction Mean Squared Errors. *International Journal of Forecasting*, 13(2):281–291.
- Henry-Nickie, M., Frimpong, K., and Sun, H. (2019). Trends in the Information Technology Sector. <https://www.brookings.edu/research/trends-in-the-information-technology-sector/>.
- Huang, L. and Wang, J. (2018). Global Crude Oil Price Prediction and Synchronization Based Accuracy Evaluation Using Random Wavelet Neural Network. *Energy*, 151:875–888.
- Huang, R. D., Masulis, R. W., and Stoll, H. R. (1996). Energy Shocks and Financial Markets. *Journal of Futures Markets*, 16(1):1–27.
- Jain, A. (2015). Machine Learning Techniques for Medical Diagnosis: A Review. In *Conference on Science Technology and Management*.

- Jammazi, R. and Aloui, C. (2012). Crude Oil Price Forecasting: Experimental Evidence From Wavelet Decomposition and Neural Network Modeling. *Energy Economics*, 34(3):828–841.
- Jang, Y., Jeong, I., and Cho, Y. K. (2020). Business Failure Prediction of Construction Contractors Using a LSTM RNN With Accounting, Construction Market, and Macroeconomic Variables. *Journal of Management in Engineering*, 36(2):04019039.
- Jones, C. M. and Kaul, G. (1996). Oil and the Stock Markets. *The Journal of Finance*, 51(2):463–491.
- Kanevski, M., Parkin, R., Pozdnukhov, A., Timonin, V., Maignan, M., Demyanov, V., and Canu, S. (2004). Environmental Data Mining and Modeling Based on Machine Learning Algorithms and Geostatistics. *Environmental Modelling and Software*, 19(9):845–855.
- Kulkarni, S. and Haidar, I. (2009). Forecasting Model for Crude Oil Price Using Artificial Neural Networks and Commodity Futures Prices. *International Journal of Computer Science and Information Security*, 2(1).
- Li, X., Shang, W., and Wang, S. (2019). Text-Based Crude Oil Price Forecasting: A Deep Learning Approach. *International Journal of Forecasting*, 35(4):1548–1560.
- Liu, J., Bai, Y., and Li, B. (2007). A New Approach to Forecast Crude Oil Price Based on Fuzzy Neural Network. In *Fourth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD 2007)*, Vol. 3, pages 273–277. IEEE.
- Mahdiani, M. R. and Khamenechi, E. (2016). A Modified Neural Network Model for Predicting the Crude Oil Price. *Intellectual Economics*, 10(2):71–77.
- Miller, M. (2019). Information Technology Sector: Overview and Funds. <https://www.valuepenguin.com/sectors/information-technology>.
- Mingming, T. and Jinliang, Z. (2012). A Multiple Adaptive Wavelet Recurrent Neural Network Model to Analyze Crude Oil Prices. *Journal of Economics and Business*, 64(4):275–286.
- Mishra, P. N., Surendran, S., Gadi, V. K., Joseph, R. A., and Arnepalli, D. N. (2017). Generalized Approach for Determination of Thermal Conductivity of Buffer Materials. *Journal of Hazardous, Toxic, and Radioactive Waste*, 21(4):04017005.
- Monnier, S. (2018). Cross-Validation Tools for Time Series. <https://medium.com/@samuel.monnier/cross-validation-tools-for-time-series-ffa1a5a09bf9>.
- Nguyen, M. (2018). Illustrated Guide to LSTM's and GRU's: A Step by Step Explanation. <https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21>.

- Nicholson, C. (2019). A Beginner's Guide to Neural Networks and Deep Learning. <https://wiki.pathmind.com/neural-network>.
- Packt (2019). Cross-Validation Strategies for Time Series Forecasting. <https://hub.packtpub.com/cross-validation-strategies-for-time-series-forecasting-tutorial/>.
- Pardeshi, S. (2019). CNN-LSTM Architecture and Image Captioning. <https://medium.com/analytics-vidhya/cnn-lstm-architecture-and-image-captioning-2351fc18e8d7>.
- Sadorsky, P. (1999). Oil Price Shocks and Stock Market Activity. *Energy Economics*, 21(5):449–469.
- Sarzaeim, P., Bozorg-Haddad, O., Bozorgi, A., and Loáiciga, H. A. (2017). Runoff Projection Under Climate Change Conditions With Data-Mining Methods. *Journal of Irrigation and Drainage Engineering*, 143(8):04017026.
- Scikit-learn (2020). Cross-Validation: Evaluating Estimator Performance. [https://scikit-learn.org/stable/modules/cross\\_validation.html](https://scikit-learn.org/stable/modules/cross_validation.html).
- Shabri, A. and Samsudin, R. (2014). Daily Crude Oil Price Forecasting Using Hybridizing Wavelet and Artificial Neural Network Model. *Mathematical Problems in Engineering*.
- Wang, J., Pan, H., and Liu, F. (2012). Forecasting Crude Oil Price and Stock Price by Jump Stochastic Time Effective Neural Network Model. *Journal of Applied Mathematics*.
- Wang, J. and Wang, J. (2016). Forecasting Energy Market Indices With Recurrent Neural Networks: Case Study of Crude Oil Price Fluctuations. *Energy*, 102:365–374.
- Xie, W., Yu, L., Xu, S., and Wang, S. (2006). A New Method for Crude Oil Price Forecasting Based on Support Vector Machines. In *International Conference on Computational Science*, pages 444–451. Springer, Berlin, Heidelberg.
- Yu, L., Wang, S., and Lai, K. K. (2008). Forecasting Crude Oil Price With an Emd-based Neural Network Ensemble Learning Paradigm. *Energy Economics*, 30(5):2623–2635.
- Yun, X. and Yoon, S. M. (2019). Impact of Oil Price Change on Airline's Stock Price and Volatility: Evidence From China and South Korea. *Energy Economics*, 78:668–679.
- Zhao, Y., Li, J., and Yu, L. (2017). A Deep Learning Ensemble Approach for Crude Oil Price Forecasting. *Energy Economics*, 66:9–16.
- Zou, Y., Yu, L., Tso, G. K., and He, K. (2020). Risk Forecasting in the Crude Oil Market: A Multiscale Convolutional Neural Network Approach. *Physica A: Statistical Mechanics and its Applications*, 541:123360.