Forecasting Short-Term Crude Oil Prices with a Deep Learning Approach

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Received: 23 March 2022; Revised: 3 April 2023; Accepted: 2 May 2023; Available online: 12 May 2023

Abstract

This paper presents a multi-layer neural network model to forecast short-term crude oil prices. The model is designed and developed for learning and analyzing the volatility of oil prices based on demand and supply fundamentals and sentiment data from online news. Potential keywords from the news regarding oil prices and price movements were grouped, pre-processed, and used as the neural network's input features. The stochastic gradient descent and regularization techniques were applied for neural learning. Designing the neural network for our study includes three models: The Fundamentals Model (FDM), Single Word Model (SWM), and Combined Word Model (CWM). Experimental results achieved show that the proposed model is promising for crude oil price forecasting for the next 1, 2, 3, and 5 days with mean absolute percentage errors of less than 3% for all test cases. There were also unnoticeable forecasting errors using demand-supply fundamentals alone and with sentiment data. However, our experiments have shown that the CWM had a higher Goodness-of-Fit to the model, and R-squared value, indicating greater predictability than the FDM and SWM models.

Keywords: Crude oil price, Sentiment data, Neural network, Short-term forecasting, Deep Feed Forward

Introduction

Crude oil remains the world's most important energy source. Refining crude oil produces various types of products for use in many industrial sectors; manufacturing, transport, foodstuff, and petrochemicals, and provides the essential energy source for industry and is a cornerstone for the development of technology as well as human society (Kamyk, Kot-Niewiadomska, & Galos, 2021; Tsiligiannis & Tsiligiannis, 2020). Crude oil price stability plays a major role in the national security and economic development of most countries, but prices tend to fluctuate due to worldwide supply and demand factors based on oil production volume, political uncertainties, and disruptions to economic activity together with fluctuations in currency exchange rates. Sentiment data related to, or from, key industries impact oil market sentiment, published in the business and popular press, and also affects price fluctuations and trends. The crude oil supply chain manifests unique business characteristics unlike those found in other commodities (Sahebi, Nickel, & Ashayeri, 2014). For example, spot prices and trading periods are set, which is a significant difference from other commodities due to the volume, transport time, and value of commodities (Zhao & Chen, 2014). As a result, risk management in the fuel oil supply chain is also important (Fernandes, Barbosa-Póvoa, & Relvas, 2010) where forward trading and float pricing fix prices for future contracts based on traders' estimates.

A review of published research related to crude oil price forecasting by using neural networks reveals techniques and methods for crude oil price forecasting that have been developed to perform analysis in diverse and uncertain circumstances. The volume of published research shows the importance of crude oil pricing and its impact on international trade, global business, and macroeconomic management (Sadik, Date, & Mitra, 2019) and the volume of research into the application of artificial intelligence techniques have been increasing steadily. Research approaches pertinent to crude oil price forecasting that are applying neural networks are following two main directions. The first direction is the development and application of forecasting tools where neural networks are being applied as a single tool or in combination with other for forecasting. The second direction concerns the features of the data available to be used in forecasting. Historical time-series data only, or in combination with data relating to other external but important factors that may affect crude oil prices, such as political and economic circumstances, extreme weather situations, and shipping shortages, as examples.

Many other researchers have analyzed the problems of crude oil price forecasting in other economic contexts because this is one important method capable of supporting planning and making purchase or sales decisions. Neural networks have been developed and applied differently in each research study on crude oil price forecasting. For example, Wang et al. (2018) developed a model for the analysis of fluctuations in data networks, combining various artificial intelligence techniques, such as the backpropagation neural network, radial basis function neural network, and extreme learning machines, to forecast crude oil prices in different time series data over days and months. Huang and Wang (2018) developed a wavelet neural network with the random time effective method by improving the reduction of errors to find a function for eliciting answers from the past data learning curve of the neural network. Forecasting techniques with neural networks have also been developed and applied to other commodity prices, such as gold prices. Alameer et al. (2019) used the Whale Optimization Algorithm to help in neural network data learning. Hu, Ni, and Wen (2020) proposed the development of the GARCH method for analyzing time-series data and building a neural network to learn data for forecasting. In agriculture, Co and Boosarawongse (2007) studied rice export volume forecasts and compared the Holt-Winters additive exponential smoothing and ARIMA methods in neural networks. Apichottanakul, Piewthongngam, and Pathumnakul (2009) studied the application of neural network methods for learning data and forecasting Thailand's global rice market share. Anggraeni, Mahananto, Sari, and Zaini (2019) also worked to forecast rice prices, in Indonesia, based on Hybrid NNs-ARIMAX by applying the ARIMAX method to the neural network to learn data for price forecasting to help the government make planning decisions and formulate policies.

Although empirical studies have found evidence that demand-supply fundamentals are correlated and affect the volatility of crude oil prices (Hui, Lo, Cheung, & Wong, 2020), sentiment data from news sources still affects the volatility of oil prices, particularly in the short term. Sentiment data can, directly and indirectly, influence the price of crude oil. For instance, when violent events or war news occur, as in the case of the news of the Gulf War or the invasion of Ukraine by Russia, there is an often dramatic effect on oil prices (Zhang, He, Zhang, & Wang, 2022). In addition, the crude oil market has experienced severe short-term fluctuations caused by the impact of the news of the COVID outbreak (Niu, Liu, Gao, & Zhang, 2021). Most studies on oil price forecasting with neural networks have begun by modeling sets of oil price data. Few studies, however, have analyzed oil price data available in unstructured formats, such as news information or opinion pieces and commentaries.

The objective of the current research was to develop an oil price forecasting system that considered demand-supply fundamentals, such as information on the oil reserves of the countries of interest, major currency exchange rates, stock indices affecting the economy, and the conditions or temperatures in countries worldwide as well as sentiment data that may affect the oil price volatility. Factors with the potential to affect oil prices derived from news sources were considered to be used as input features for crude oil price forecasting by the neural network with WTI (West Texas Intermediate) and Brent Crude Oil Spot Price as sample data. This research presents the commodity price forecasts using a case study of crude oil prices by combining the analysis of information on various sources of data including news from online media and social media for price forecasting to make decisions and manage the risks in crude oil trading by applying the neural network model. Many studies use ANNs to predict crude oil prices based on time series using historical price data as a predictive price-influencing feature. A popular Long Short-Term Memory Neural Network (LSTM) is applied to sequential data (Busari & Lim, 2022; Zhang & Hong, 2022) so that the model learned the pattern of past price fluctuations for forecasting. CNN and LSTM were also used to forecast crude oil prices using stock prices of leading information technology companies as features (Assaad & Fayek, 2022).

Several studies have shown that news is an important source of information that can measure changes in market sentiment (Li, Jiang, Li, & Wang, 2021; Niu, Liu, Gao, & Zhang, 2022). In addition, it can enhance the accuracy of forecasting short-term stock returns (Bai, Li, Yu, & Jia, 2022), which is crucial for business policymakers and investors to manage the risk. This research considers demand-supply information, key economic factors, sentiment data from publicly accessible online news, and crude oil price one day earlier to forecast short-term oil prices, which is different from the research mentioned above. Because the price of crude oil fluctuates and changes every day, forecasts based on long-term historical data may not support sharp daily price fluctuations. Also, storing data in the past takes a lot of time and resources and may not be suitable for organizations that are not ready to prepare large amounts of data.

The rest of the paper is organized as follows. The Methods and Materials section presents the data preparation, including how to extract sentiment data from online news and social media, make news dictionaries, and analyse the sentiments. It also presents the design of a neural network considering both demand-supply fundamentals and sentiment data. The crude oil price forecasting and experimental results are described in the Experimental Results section. Finally, Conclusions are given.

Methods and Materials

Data preparation

The fundamental factors that were considered included the following: oil production capacity, oil imports of major countries (US, China, India), exchange rates of major world currencies (EUR, USD, GBP, CNY), major world stock market indices, and temperatures of major oil-importing countries. This information can be found online.

Preliminary data processing from comments and sentiments obtained from online news and social media was divided into three steps, starting by creating the news dictionary, compiling, and then splitting the words and assigning weightings to the sentiment expressions.

Creating the news dictionary

The database for storing and collecting keywords that may affect crude oil prices was developed to provide the initial data for the crude oil price short-term forecasting model that was being developed. The first step was to create expert-sourced keywords to be used to filter interesting news and content relevant to crude oil prices from the news sources, then use that news content for analysing the probability of oil price increases or decreases. Tables 1, 2 and 3 show examples of keywords that may result in oil prices going up or down.

Table 1 Keywords for filtering news that may affect the oil prices

Filtering Words						
oil facilities	oil & gas	oil contract	oil transaction	oil industry	oil and gas	oil and natural gas
oil company	oil fields	oil tanker	refined products	gasoline price	VLCC	WTI
petroleum	refinery	refineries	brent	cents per gallon	crude	hedging
fossil	coal	drill	geopolitics	LNG market	traders	quotas
levy	levies	shale oil	oil price	oil product	oil export	oil import
Oil trader	oil inventory	oil inventories	oil pipeline	oil price	bpd	supertanker
tanker	fuel	LNG	barrel	OPEC	Platts	pipeline
hedge	US election	US energy	vessel	energy	pumping	tariff
tensions	sanction	UK election	liquefied natural gas	oilfield	UAE	Aramco
US shale						

Table 2 Keywords that may result in oil prices going up (increase)

Examples of Keywords						
explosion	war	trade deal	explode	explosive	gas pipeline attack	oil export drops
erupt	slash	cartel	interruption	interrupt	crude oil imports rise	shuts in production
brake	dispute	shut down	turbulent	OPEC cut	oil consumption growth	oil demand growth
fear	ties	warning	tragedy	gulf storm	oil inventories fall	oil production drop
worsen	halt	hurricane	threaten	snowstorms	strong opposition	pipeline explosion
surge	impede	strike	trading up	cut production	oil inventory draw	production cut
flood	worse	rebound	flooding	protests	wildfire	demand growth
protestor	tragedy	supply cut	troops	earthquake	oil market bull	oil import jump

Table 3 Keywords that may result in oil prices going down (decrease)

Examples of Keywords					
ease	expedite	ramp up exports	shale boom	economic slowdown	oil refinery jumps
agree	negotiate	negotiation	oil inventory build	commerce slowdown	boost oil production
deal	crude fell	crude drop	boost shale output	lower demand for crude	oil field development
recession	oil slip	trade war	production boom	increase cooperation	boost production
sluggish	run cut	greenlight	refineries trim	oil production fall	slowing economic
handshake	optimism	boost crude	trade tension	rig count fall	consumption sluggish
agreement	crude build	export surges	production boom		

In addition, we considered the geopolitical impact (Geo-politics) by creating a data dictionary with the names of countries with crude oil production capacity and crude oil trading partners for weighting the news. There were two types in the data dictionary. As illustrated in Table 4, the crude oil production of each country (Oil production) was considered important and relevant, and the values of international crude oil trading (Trade flow), as shown in Table 5. The data analysis process will be explained in Section 3.3.

Table 4 Crude oil production of each country (Oil production)

Country	Oil Production (BBL/day)
United States	15,043,000
Saudi Arabia	12,000,000
Russia	10,800,000
Iraq	4,451,516
Iran	3,990,956
China	3,980,650
Canada	3,662,694
United Arab Emirates	3,106,077
Kuwait	2,923,825
Brazil	2,515,459

Table 5 Values of international crude oil trading (Trade flow)

Trading Partner Countries		Values (USD Billion)
Canada	United States	350
United States	European Union	655
China	Hong Kong	250
Mexico	United States	269
China	European Union	663
China	United States	510

Newsgathering

API data was requested from service providers such as Twitter or Google news. Then, using a web crawler technique in a software product known as Web-spider (Dikaiakos, Stassopoulou, & Papageorgiou, 2005; Stevanovic, An, & Vlajic, 2012), data was collected from public online news, such as Oilprice.com and BBC news with no API service. The search-spider was used for exploring, reading, and retrieving web page data from various domains, allowing us to automatically retrieve the interesting data required. The data obtained include news sources, news dates and times, news headlines and news content. The news information obtained was in the form of unstructured text as well as sentences.

Word splitting and weighting

Having obtained news information using Web-spider, the next process was data cleansing. In this first step, all letters were changed to lowercase and the apostrophe words, such as "I'm", were changed to "I am" as appropriate. Special symbols and numbers were removed. The next process was to split words according to the data dictionary and calculate the weight of the words or set of words that express sentiments.

Table 6 Notations

Parameters	Description
C	set of crude oil producers in Table 4
P	set of trading partners in Table 5
K	set of sentiment keywords (increase and decrease keywords)
N	set of the news.
q_k^n	frequency of keyword k in news n, where $k\epsilon K$ and $n\epsilon N$
w_k^n	weight of keyword k in the news n
o_c	crude oil production of country c, where $c\epsilon C$
t_p	value (USD billion) of trading partner counties p, where $p\epsilon P$
wo_c	weight of country c with crude oil production
wt_p	weight of trading partner p
wo_c^n	weight of country c with crude oil production in the news n, $wo_c^n = wo_c$ if finding the country c mentioned in the news n or $wo_c^n = 0$ otherwise.
wt_p^n	weight of trading partner p in the news n, $wt_p^n = wt_p$ if a partner country is found, p appears in the news n or $wt_p^n = 0$ otherwise.

Step 1: Filter relevant news about crude oil prices using keywords from Table 1. If there is at least one keyword in the news, then the sentiment keyword weight will be calculated.

Step 2: Calculate the weight for each country from the equation.

$$wo_c = o_c / \max_{c\in C} o_c \quad ; \ \forall c\epsilon C$$

where $\max_{c\in C} o_c$ is the greatest production of crude oil

Step 3: Calculate the weight for each trading partner from the equation.

$$wt_p = t_p / \max_{p\epsilon P} t_p \quad ; \ \forall p\epsilon P$$

where $\max_{p\epsilon P} t_p$ is the greatest value of the trading partner.

Step 4: Check the list of countries from the news and calculate w_k^n under the conditions.

Case 1: If there is a list of trading partners p from Table 5 for both countries in news n where $\sum_{p\in P} wt_p^n > 0$, so w_k^n is calculated as follows:

$$wt^n = \max_{p\epsilon P} wt_p^n$$

$$w_k^n = (1 + wt^n) \times q_k^n$$

Case 2: In the absence of the list of trading partners, but is a crude oil producer and appears in news n where $\sum_{p\in P} wt_p^n = 0$ and $\sum_{c\in C} wo_c^n > 0$, so w_k^n is calculated as follows:

$$wc^n = \max_{c\in C} wo_c^n$$

$$w_k^n = (1 + wc^n) \times q_k^n$$

Case 3: If not found in the list of trading partners and not crude oil producers where $\sum_{p\in P} wt_p^n + \sum_{c\in C} wo_c^n = 0$, so w_k^n is calculated as follows:

$$w_k^n = 0.5 \times q_k^n$$

Step 5: Finally, combine the frequency of words and record the data according to the equation below.

$$w_k = \sum_{n\in N} w_k^n \quad ; \ \forall k\epsilon K$$

Neural network design

The design process for the neural network for the current study included three models: the demand-supply fundamentals alone, called the Fundamentals Model (FDM), and the FDM with the weights of the news dictionary, with each word as an input feature for the model learning, called the Single Word Model (SWM), and the FDM with the sum of weighted values of the news dictionary for oil price increases and oil price decreases, called the Combined Word Model (CWM). The number of FDM features was 14 inputs. In SWM, the number of features was 104 inputs and there were 16 inputs for features for CWM. Overall, there were 54 words treated as increase features and 36 words treated as decrease features).

The neural network was tested by comparing the number of hidden layers and nodes in each hidden layer. These values affect the number of parameters to learn and the accuracy of the forecast. Too many hidden layers can result in the problems of vanishing or exploding gradients. The most effective number of hidden layers is that which requires less learning time and forecasting errors. Four hidden layers and nodes in each layer should not be less than the number of feature input layers. On the contrary, increasing the number of nodes will affect the learning time. By testing the activation function in the last hidden layer, the sigmoid function is suitable. In other hidden layers, the ReLU function is assigned for the model's learning speed. The neural network for testing the results of the oil price forecast was derived, namely Input → 256 → ReLU → 128 → ReLU → 128 → ReLU → 64 → sigmoid → Output. The loss function was the Mean Square Error (MSE) for the model learning and evaluating the forecasting results.

The neural network has more hidden layers and nodes. Therefore, this part used an optimization algorithm that adjusted the learning rate and resolved the decaying learning rate, namely Adaptive Moment Estimation (Adam) (Kingma & Ba, 2015). Also, the stochastic gradient descent was applied to determine the batch size in each learning epoch to increase the speed of learning and reduce the local minimum. Additionally, the learning process applied a regularization technique by specifying early stopping to reduce generalization errors. This is illustrated in Figure 1 which shows the errors of the training data set (loss) compared with the validation data set (val_loss) and the mean absolute error (mae) that started to increase when the model learned and was overfitted with the training data set.

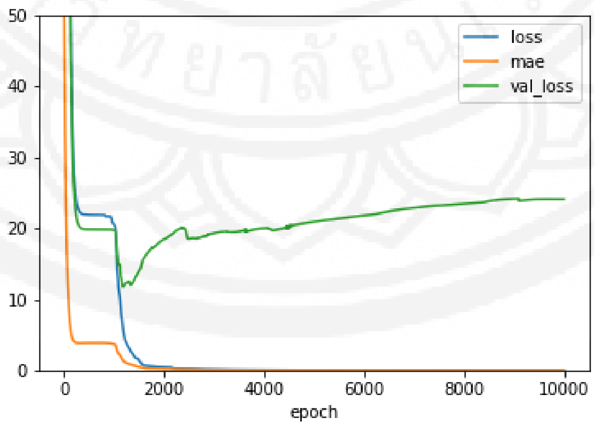
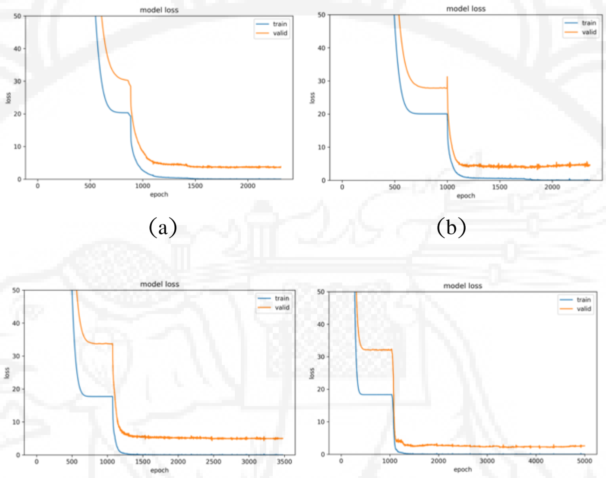


Figure1 Errors with the validation data set from overfitting

Experimental Results

Forecasting results were based on Brent crude data from 1 January 2019 to 31 October 2019. The data were divided into training data for the model (70% of the available data), and testing data (30% of the available data). During model learning, 20% of the training model data set was used for validation. In the testing set, 3,000 epochs were set as the number of learning epochs. To reduce the error when processing beyond the stipulated epochs, the specified early stopping condition was 250 epochs when the model failed to learn. To show the errors in the learning process and to compare each model, the test includes learning and forecasting crude oil prices for 1, 2, 3, and 5 days ahead. For the Single Word Model (SWM), the errors in learning epochs are shown in Figure 2.

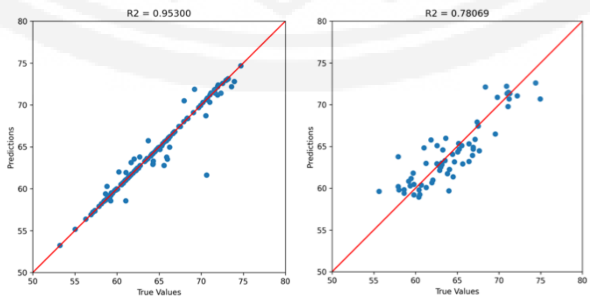


(a) (b)

(c) (d)

Figure 2 SWM learning cycle errors

Figure 2 shows the errors in the learning epochs of SWM. The training line (blue) is the MSE of learning the training data set and the valid line (orange) is the MSE of the validation data set randomized from the training data set, setting 20% to verify the learning model's accuracy and to be a condition for stopping learning when the error values do not decrease in the given epochs. Noticeably, Figure 2(a) shows the errors of learning epochs for the next 1-day oil price forecast which stops learning before completing 3,000 specified epochs, and Figures 2(b), (c) and (d) show the errors of learning epochs in forecasting oil prices in the next 2-day, 3-day and 5-day periods which also stops learning before completion.



(a) (b)

Figure 3 Prediction error distribution from SWM

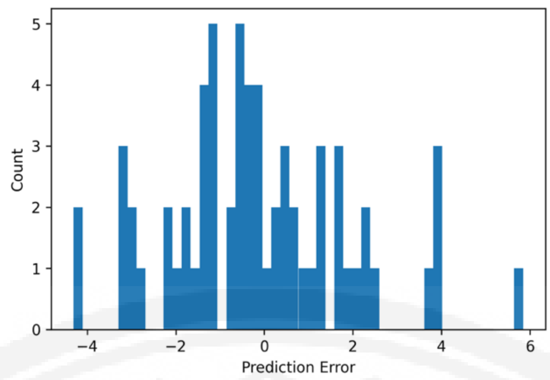
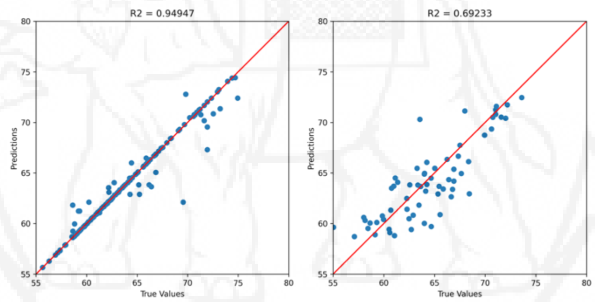


Figure 4 Prediction error values distribution from SWM

Figure 3 shows the variation between 1-day forecasts and the next-day actual oil prices of SWM, while 3(a) shows the variation between the forecasting values and oil prices from the training data set and 3(b) shows the variation between the forecasting values and actual oil prices from the testing data set. Figure 4 shows the distribution of errors, forecasting values, and actual oil prices in the testing data set (unseen). For the forecasting errors in the training data set, the MSE was 0.0074 and MAPE was 0.105%. For the forecasting errors in the validation data set, the MSE was 5.038 and MAPE was 2.438%. For the forecasting errors in the testing data set, the MSE was 4.176 and MAPE was 2.506%.



(a) (b)

Figure 5 Variation of 2-day forecasts and the next 2-day SWM oil prices

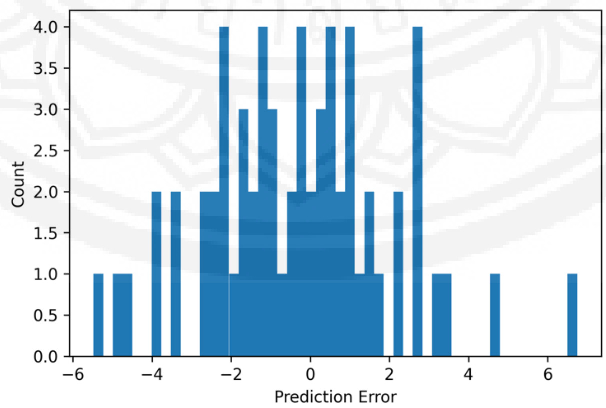
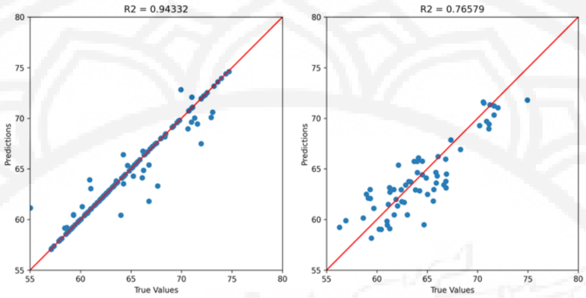


Figure 6 Prediction error distribution from SWM (next 2-day period)

Figure 5 shows the variation between 2-day forecasts and the next 2-day actual oil prices of SWM, while 5(a) shows the variation between the forecasting values and oil prices from the training data set, and 5(b) shows the variation between the forecasting values and actual oil prices from the testing data set. Figure 6 shows the distribution of errors, forecasting values, and actual oil prices in the testing data set. For the forecasting errors in the training data set, the MSE was 0.0042 and MAPE was 0.061%. For the forecasting errors in the validation data set, the MSE was 5.427 and MAPE was 2.757%. In addition, for the forecasting errors in the testing data set, the MSE was 5.366 and MAPE was 2.833%.



(a) (b)

Figure 7 Variation of 3-day forecasts and the next 3-day SWM oil prices

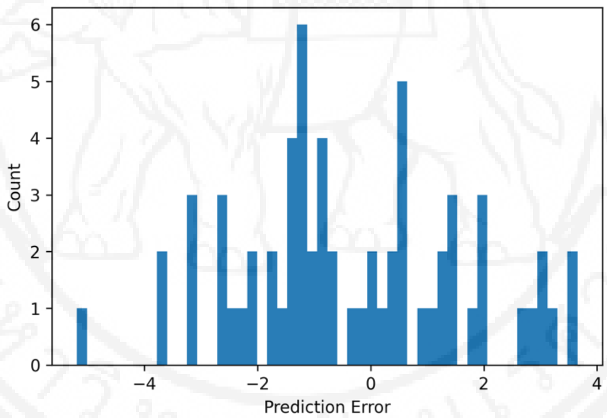
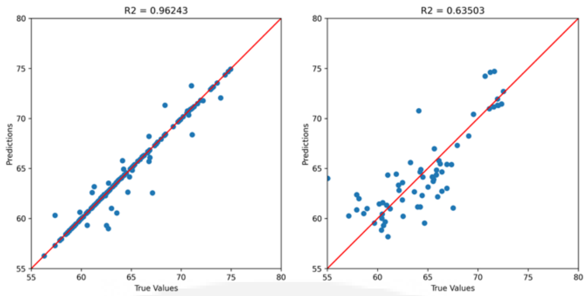


Figure 8 Prediction error distribution from SWM (next 3-day period)

Figure 7 shows the variation between 3-day forecasts and the next day's actual oil prices of SWM, while 7(a) shows the variation between the forecasting values and oil prices from the training data set and 7(b) shows the variation between the forecasting values and actual oil prices from the testing data set. Figure 8 shows the distribution of errors, forecasting values, and actual oil prices in the testing data set. For the forecasting errors in the training data set, the MSE was 0.0021 and MAPE was 0.051%. For the forecasting errors in the validation data set, the MSE was 6.023 and MAPE was 3.015%. For the forecasting errors in the testing data set, the MSE was 3.976 and MAPE was 2.609%.



(a) (b)

Figure 9 Variation of 5-day forecasts and the next 5-day SWM oil prices

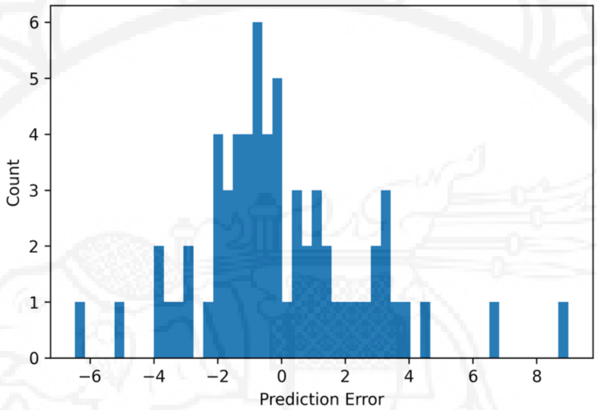
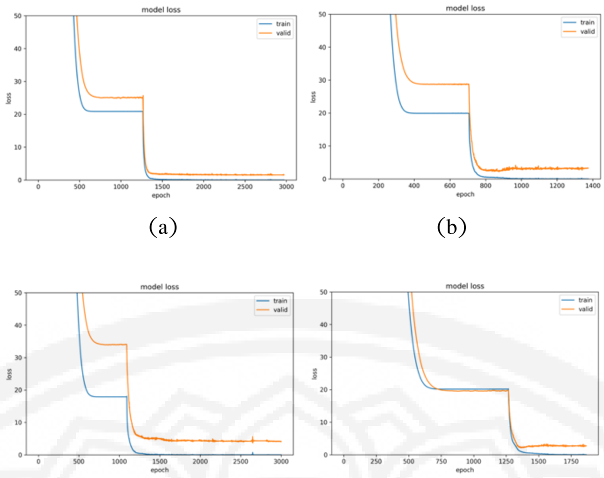


Figure 10 Prediction error distribution from SWM (next 5-day period)

Figure 9 shows the variation between 5-day forecasts and the next-day actual oil prices of SWM, while 9(a) shows the variation between the forecasting values and oil prices from the training data set and 9(b) shows the variation between the forecasting values and actual oil prices from the testing data set. Figure 10 shows the distribution of errors, forecasts, and actual oil prices in the testing data set. For the errors in the training data set, the MSE was 0.0019 and MAPE was 0.052%. For the forecasting errors in the validation data set, the MSE was 3.736 and MAPE was 2.323%. For the errors in the testing data set, the MSE was 6.768 and MAPE was 3.067%.

Testing the combined word model (CWM) in learning and forecasting oil prices in the next 1, 2, 3, and 5 days, which is considered short-term forecasting within less than one week, by showing errors of the model's learning periods and displaying errors when forecasting in the training data set (seen) and testing data set (unseen) can be observed as follows.

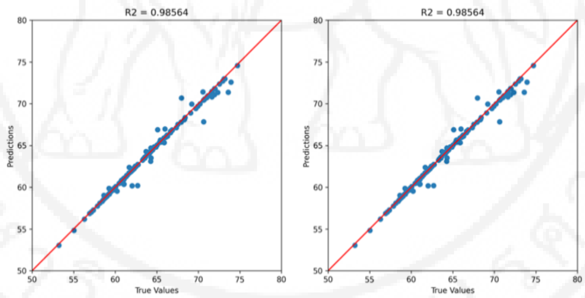


(a) (b)

(c) (d)

Figure 11 CWM learning cycle error

Figure 11 shows errors in the learning epochs of CWM. The training line (blue) is the MSE of the training data learning and the valid line (orange) is the MSE of the validation data set, randomly chosen from the training data set. This is set to 20% to verify the learning model's accuracy and to be a condition for the stopping criteria when the errors do not decrease in the given epochs. Figures (a) (b) (c) and (d) show the forecasting errors in the 1-day, 2-day, 3-day, and 5-day periods ahead. For all models, learning stops before completing the specified total number of epochs.



(a) (b)

Figure 12 Variation of 1-day forecasts and the next-day CWM oil prices

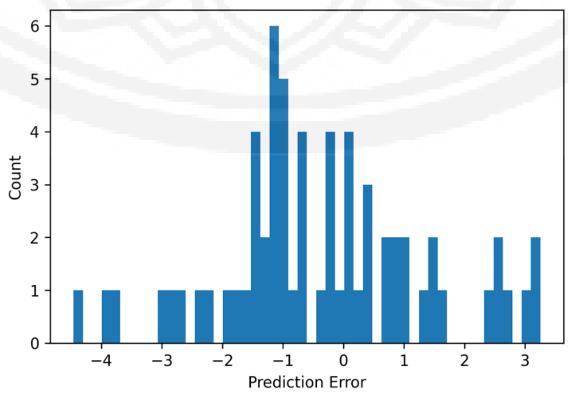
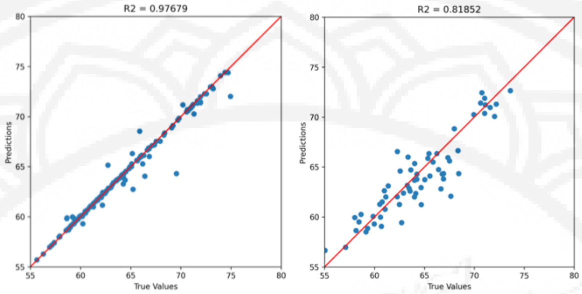


Figure 13 Prediction error distribution from CWM

Figure 12 shows the variation between 1-day forecasts and the next 1-day actual oil prices of CWM, while 12(a) shows the variation between the forecasting values and oil prices from the training data set and 12(b) shows the variation between the forecasts and actual oil prices from the testing data set. Figure 13 shows the distribution of errors, forecasts, and actual oil prices in the testing data set. For the errors in the training data set, the MSE was 0.0108 and MAPE was 0.118%. For the errors in the validation data, the MSE was 1.502 and MAPE was 1.445%. Finally, for the forecasting errors in the testing data set, the MSE was 2.959 and MAPE was 2.131%.



(a) (b)

Figure 14 Variation of 2-day forecasts and the next 2-day CWM oil prices

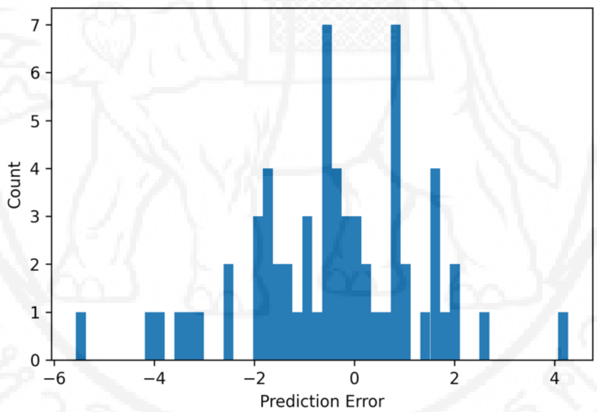
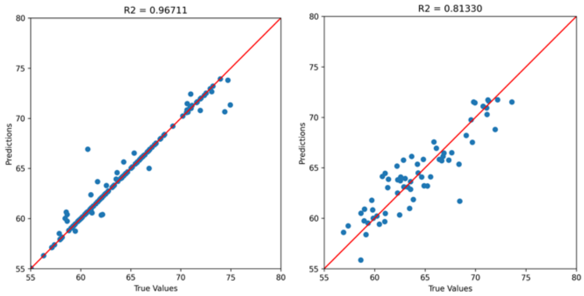


Figure 15 Prediction error distribution from CWM (next 2-day period)

Figure 14 shows the variation between 2-day forecasts and the next 2-day actual oil prices of CWM, while 14(a) shows the variation between the forecasting values and oil prices from the training data set and 14(b) shows the variation between the forecasting values and actual oil prices from the testing data set. Figure 15 shows the distribution of errors, forecasting values, and actual oil prices in the testing data set. For the forecasting prices in the training data set, the MSE was 0.0067 and MAPE was 0.088%. For the errors in the validation data set, the MSE was 2.470 and MAPE was 1.696%. Finally, for the errors in the testing data set, the MSE was 3.165 and MAPE was 2.120%.



(a) (b)

Figure 16 Variation of 3-day forecasts and the next 3-day CWM oil prices

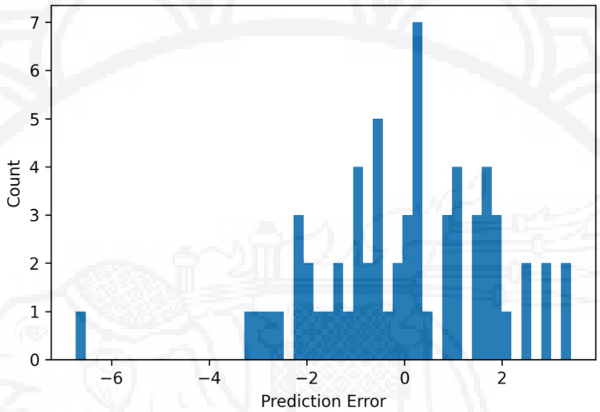
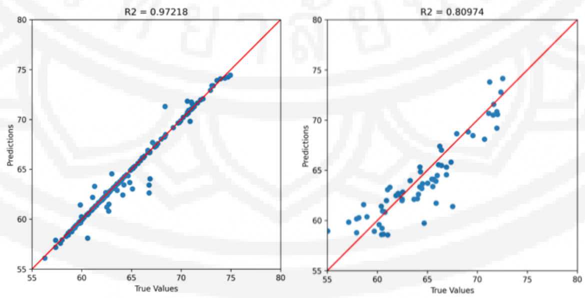


Figure 17 Prediction error distribution from CWM (next 3-day period)

Figure16 shows the variation of 3-day forecasts and the next 3-day actual oil prices of CWM, while 16(a) shows the variation between the forecasts and oil prices from the training data set and 16(b) shows the variation between the forecasting values and actual oil prices from the testing data set. Figure 17 shows the distribution of errors, forecasts, and actual oil prices in the testing data set. For the errors in the training data set, the MSE was 0.0003 and MAPE was 0.020%. For the errors in the validation data set, the MSE was 3.455 and MAPE was 2.116%. For the errors in the testing data set, the MSE was 3.279 and MAPE was 2.205%.



(a) (b)

Figure 18 Variation of 5-day forecasts and the next 5-day CWM oil prices

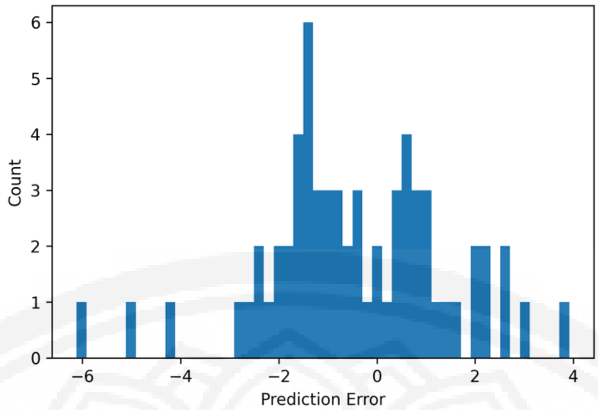


Figure 19 Prediction error distribution from CWM (next 5-day period)

Figure 18 shows the variation between 5-day forecasts and the next 5-day actual oil prices of CWM, while 18(a) shows the variation between the forecasting values and oil prices from the training data set and 18(b) shows the variation between the forecasting values and actual oil prices from the testing data set. Figure 19 shows the distribution of errors, forecasting prices, and actual oil prices in the testing data set. For the errors in the training data set, the MSE was 0.0109 and MAPE was 0.111%. For the errors in the validation data set, the MSE was 2.719 and MAPE was 1.994%. Finally, for the errors in the testing data set, the MSE was 3.528 and MAPE was 2.348%.

Table 7 Forecasting errors of each model

Model	Day	#Param	Train		Validate		Test		
			MSE	MAPE	MSE	MAPE	MSE	MAPE	R^2
FDM	1	61,598	0.0146	0.155	3.841	2.085	2.703	**2.038***	**0.846***
FDM	2	61,598	0.0175	0.159	4.099	2.183	3.788	2.352	0.784
FDM	3	61,598	0.0006	0.024	4.982	2.541	4.451	2.381	0.742
FDM	5	61,598	0.0001	0.009	2.569	1.758	3.633	**2.241***	0.791
SWM	1	84,609	0.0074	0.105	5.038	2.438	4.176	2.506	0.781
SWM	2	84,609	0.0042	0.061	5.427	2.757	5.366	2.833	0.692
SWM	3	84,609	0.0021	0.051	6.023	3.015	3.976	2.609	0.766
SWM	5	84,609	0.0019	0.052	3.736	2.326	6.768	3.067	0.635
CWM	1	62,081	0.0108	0.118	1.502	1.445	2.959	2.131	0.845
CWM	2	62,081	0.0067	0.088	2.470	1.696	3.165	**2.120***	**0.819***
CWM	3	62,081	0.0003	0.020	3.455	2.116	3.279	**2.205***	**0.813***
CWM	5	62,081	0.0109	0.111	2.719	1.994	3.528	2.348	**0.810***

Table 7 compares the forecasting errors between methods in each learning process: Train, Validate and Test with 1, 2, 3 and 5-day forecasts. The #Param is the number of parameters of the model's learning. The MSE is the mean square error, which is the error function used in learning, and MAPE is the mean absolute percentage error.

Conclusion and Discussion

In this paper, we have developed forecasting models for short-term crude oil prices. Apart from a classical demand-supply fundamental forecasting technique, we consider sentiment data built up in the artificial neural network model in forecasting crude oil prices. The unstructured sentiment data, trawled from the web, were converted into a standardized format. They were used as input features in the neural network model by creating and weighting keywords that may affect the oil prices. The Adam, adaptive learning rate algorithm, is used to optimize input features and hidden layers in the network. The stochastic gradient descent and regularization techniques were included for neural network learning. Three proposed neural network models were evaluated: fundamentals model (FDM) without sentiment data, FDM with sentiment data, single word model (SWM) and FDM with sentiment data, and combined word model (CWM).

In the model structure, the SWM has more learning parameters than CWM. As a result, the forecasting errors of SWM in both the validation and testing of data sets were greater than those of CWM. This is possibly due to more input features or keywords making the model more complicated, affecting oil prices going up and down in an unclear direction. It can be noted also that the CWM presents more errors with longer forecasting periods. As for the observation from the learning model in 5-day oil price forecasts, the model has MSE and MAPE less than for the 2-day forecasts in the training data set. However, with the testing data set, the errors in the 5-day forecasts were greater than those of the 2-day and 3-day forecasts. With a longer forecasting period, the models were less accurate accordingly.

When FDM (without sentiment data) and CWM were compared, the errors, and MSE and MAPE of FDM in the testing data set were slightly less than CWM. This may be because the consideration of keywords, phrases, and sentiments from online news does not help explain the fluctuation in oil prices. Online news using sentiment analysis may require the content of the entire news article, instead of considering particular keywords or phrases separately. However, CWM has higher values of R-squared indicating greater predictability of the model.

Our proposed neural network model with and without sentiment data is flexible for future improvements and modifications, is less complex, and does not consume a lot of computer resources (e.g., central processing unit or processing time) for learning. It is suitable for organizations that are unable to collect data or lack the resources to store large amounts of data. The forecasting results obtained from the proposed method can also be used in planning and risk assessment for these organizations. This results in the ability to develop the model and the system in long run, including assessing the performance of the forecasting model from loss function to guide the development of forecasting systems which can be used in various industries.

Acknowledgements

This research is supported by grant no. 02/2563 from the Faculty of Logistics, Burapha University, Chonburi, Thailand. We would like to thank crude oil trading experts from the national oil company of Thailand for help in the experimental setup. We also thank Mr Roy I. Morien, Language Specialist, of the Naresuan University Graduate School, for his editing of the grammar, syntax and general English expression in this manuscript.

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